Defects and Statistical Degradation Analysis of Photovoltaic Power Plants

by

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ABSTRACT

As the photovoltaic (PV) power plants age in the field, the PV modules degrade and generate visible and invisible defects. A defect and statistical degradation rate analysis of photovoltaic (PV) power plants is presented in two-part thesis. The first part of the thesis deals with the defect analysis and the second part of the thesis deals with the statistical degradation rate analysis. In the first part, a detailed analysis on the performance or financial risk related to each defect found in multiple PV power plants across various climatic regions of the USA is presented by assigning a risk priority number (RPN). The RPN for all the defects in each PV plant is determined based on two databases: degradation rate database; defect rate database. In this analysis it is determined that the RPN for each plant is dictated by the technology type (crystalline silicon or thin-film), climate and age. The PV modules aging between 3 and 19 years in four different climates of hot-dry, hot-humid, cold-dry and temperate are investigated in this study.

In the second part, a statistical degradation analysis is performed to determine if the degradation rates are linear or not in the power plants exposed in a hot-dry climate for the crystalline silicon technologies. This linearity degradation analysis is performed using the data obtained through two methods: current-voltage method; metered kWh method. For the current-voltage method, the annual power degradation data of hundreds of individual modules in six crystalline silicon power plants of different ages is used. For the metered kWh method, a residual plot analysis using Winters' statistical method is performed for two crystalline silicon plants of different ages. The metered kWh data typically consists

of the signal and noise components. Smoothers remove the noise component from the data by taking the average of the current and the previous observations. Once this is done, a residual plot analysis of the error component is performed to determine the noise was successfully separated from the data by proving the noise is random.

To,

Latha Sundar, R.Sundarajan (my mother and father), Priya Sundarajan (sister) T.M. Thirumalai and T.M. Vaidhehi (grandparents), Srinivasa Sundararajan and Geetha Sundar (uncle and aunt) for their constant love, motivation and the trust they had on me.

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PART 1: DEFECT ANALYSIS OF PV POWER PLANTS

1.1 INTRODUCTION

1.1.1 Background

In today's Solar PV industry, mitigation of performance losses due to defects found in power plants is of extreme importance. Based on the paper published by M.A.Quintana et.al [1], Neelesh et.al [12] summarized that the degradation of photovoltaic modules in the field could be due to the type of environment the modules are being exposed to, manufacturing problems and quality of the design of the PV panels. The degradation modes would cause the degradation of I-V parameters (Fill Factor, Open Circuit Voltage, and Short Circuit Current) which eventually leads to the loss of the output power of a module. This degradation could be caused by single or multiple modes of degradation. The number of panels which are being installed every year seem to be increasing at an exponential rate. This therefore creates a compulsive need to quantify the different risks posed by these defects to the performance (degradation) of the power plants present in different climatic conditions. This quantification of the risks associated to one particular defect was determined using the Risk Priority Number (RPN) technique developed by Shrestha et.al. [3]. Shravanthi et.al [15] and Vidhya et.al [14] further classified The RPN is classified into three further categories: Safety RPN (S-RPN), Performance RPN (PRPN) and Global RPN (G-RPN). In this thesis, we have focused particularly on global RPN. Shrestha et.al [13] reported in his thesis that this method uses the Risk Priority number Techniques to Rank the failure modes. The highest RPN number is assigned to the failure mode which poses the worst risk and cause performance losses. RPN helps in quantifying the performance losses (or degradation) caused due to a particular defect found in the power plant. A database of RPN will help manufacturers and power plant owners to determine the manufacturing or design inadequacies. Using this knowledge, modules which are reliable to those particular defects can manufactured as reported by Shrestha et.al [13]. Using the MATLAB code developed by Mathan et.al [4] which automates the calculation of the RPN using a program based on mathematical formulas for finding RPN, a database of RPN plots and Degradation rates correlated with defective modules was created. This involved gathering the Visual inspection data gathered from power plant visits which tells us the presence/absence of a defect in a module and this data is correlated to the I-V data. These two file produce an output data correlation file which quantifies the loss of performance of the module due to the defect present in it.

Using this data correlation file and RPN plots, a database consisting of the all the defects found in the USA across power plants in different climatic conditions was created. Once the database was created and every defect in each climatic condition had been listed, we would be able to come up with a database for the dominant defects affecting performance of power plants in each climatic conditions and their corresponding Risk priority numbers. The goal of this part of the thesis is to:

- Develop an automated database for defects found in the power plants across different climatic conditions and examine if the RPN is dictated by technology type, climate and age.
- Create a database for all the defects by detecting, analyzing and summarizing the defects found in different climatic conditions.

- Determining the dominant defect observed in each climatic condition across the USA and assign a corresponding RPN number to reflect the possible financial risks the dominant defects is posing to the power plants.

1.1.2 Statement of Problem:

Using the technology and data available at ASU-PRL, data for 14 power plants in the USA was gathered and various output results were obtained using the MATLAB code developed by Mathan et.al [4]. The defects were correlated with the rate of degradation of performance parameters and Pmax degradation obtained for 14 power plants whereas the RPN plots were obtained for 10 power plants since 4 power plants had no defects. With such a wide database, we try to answer the pressing questions in today's industry which are stated below.

1. Establish the defects affecting the Pmax degradation for two weather conditions such as hot and dry and cold and dry by statistically analyzing multiple power plants and assigning RPN to each of the performance defects found in these power plants.
2. Determine dominant defects in each climatic condition and assigning an RPN to quantify each defect so that manufacturers and investors can come up with climate specific accelerated tests to mitigate the effects of dominant defects. This also creates a possibility to also develop defect specific accelerated tests for the most dominant defects which is independent of the climate.

1.1.3 Objective

Evaluation of a PV power plant and performing RPN analysis on the defects in PV power plant used to be carried out manually. Manual evaluation is time consuming and involves lot of manual labor to perform these analyses. In order to overcome this, it is better to automate the process which was done by Mathan et.al [4], where a RPN program in MATLAB was created to automatically calculate the Global RPN. Using this automated process and the vast amount of data available at ASU-PRL, it is possible to come up with a database for the performance of power plants and the defects affecting them in different weather conditions across the USA along with the associated risk of the defect being provided by the RPN. It also helps PV power plant owners to identify the modules with failures and understand the failure modes causing it. This helps design climate specific accelerated tests to mitigate the effect of particular defects. When multiple power plants in each weather condition is analyzed and the dominant failure modes are determined, we would end up with a database which could be used by the power plant owners to make decisions on the power plants (retain/sell/buy).

1.2 LITERATURE REVIEW

1.2.1 Safety, Reliability and Durability failures:

Tamizhmani et.al [5] defined failures as "If the PV modules are removed (or replaced) from the field before the warranty period expires due to any type of failure, including power drop beyond warranty limit, then those failures may be classified as hard failures. In other words, all failures that qualify for warranty returns may be called a reliability failure. If the performance of PV modules degrades but still meets the warranty requirements, then those losses may be classified as soft losses or degradative losses. Toward the end of the module's life, multiple degradative mechanisms may develop and lead to wear-out failures due to accelerated degradative losses". Figure 1 shows the metric definitions for safety failure, reliability failure, and durability loss.

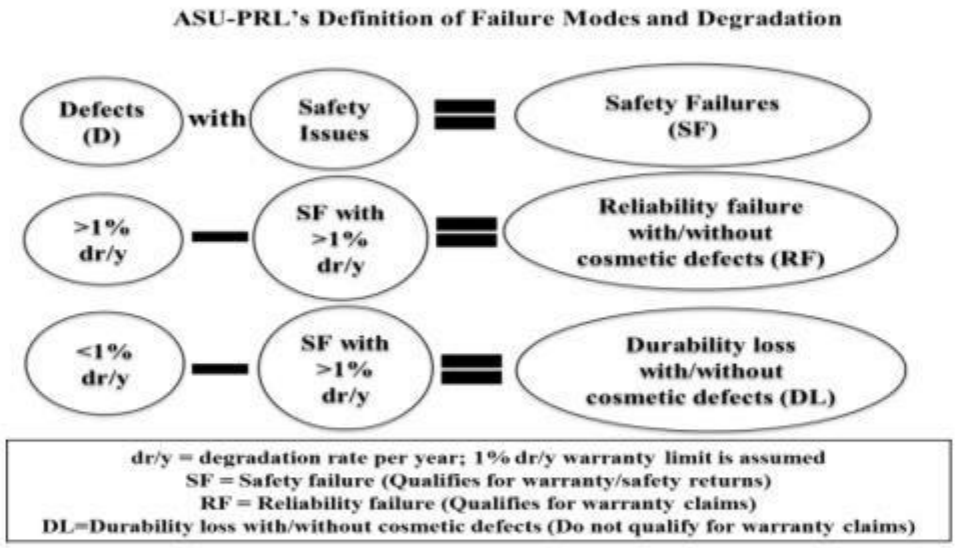


Figure 1: metric definitions of failures

1.2.2 Defects/Failures found in PV Modules

Investors and power plant owners looking to buy power plants or thinking if they should retain or sell the existing plant can make such decisions based on two designed parameters, (1). Rate of degradation correlated to the Defects observed visually in the power plant with their corresponding RPN. With the information obtained from these calculated parameters, we can say if the power plant is healthy or not. We do this statistically by using the Risk Priority Number program which can tell the investor/owner if the dominant defect observed is harmful or not. Risk priority number (RPN) for each defect/failure is automatically generated based on visual inspection spreadsheet (VI). Automation program package developed by Mathan et.al [4] involves two major programs – one which is used to calculate the global RPN and other is to find the modules with defects and their correlation with IV parameters degradations. The goal of the project is to create a database for RPN using the global RPN program (safety RPN + Performance RPN) for 10 power plants evaluated by ASU-PRL. Investors can use this as a guide which tells them the dominant defects in each weather condition and the defects observed in two weather conditions along with the corresponding risks associated to those defects using the RPN for each defect. Based on the information we obtain from RPN, the plant owners will be able to make warrantee entitlements from the manufacturer and also to decide whether it would be profitable to retain the power plant or not.

The correlation program uses two excel spreadsheets: the degradation spreadsheet (IV) and the defects spreadsheet (VI). The correlation program detects the modules with performance defects and correlates the corresponding degradation of performance parameters (rate of degradation of Isc, Voc, FF, etc.). This correlation is generated as an output excel file called the data correlation file. The data correlation was done for 15 power plants. A database for Pmax degradation for power plants in four different climatic conditions. A database for the degradation of 4 performance parameters (Isc, Voc, FF and Rs) was created in order to serve as a database for future research work into the performance parameters of power plants.

1.3 METHODOLOGY

1.3.1 Visible and invisible defects

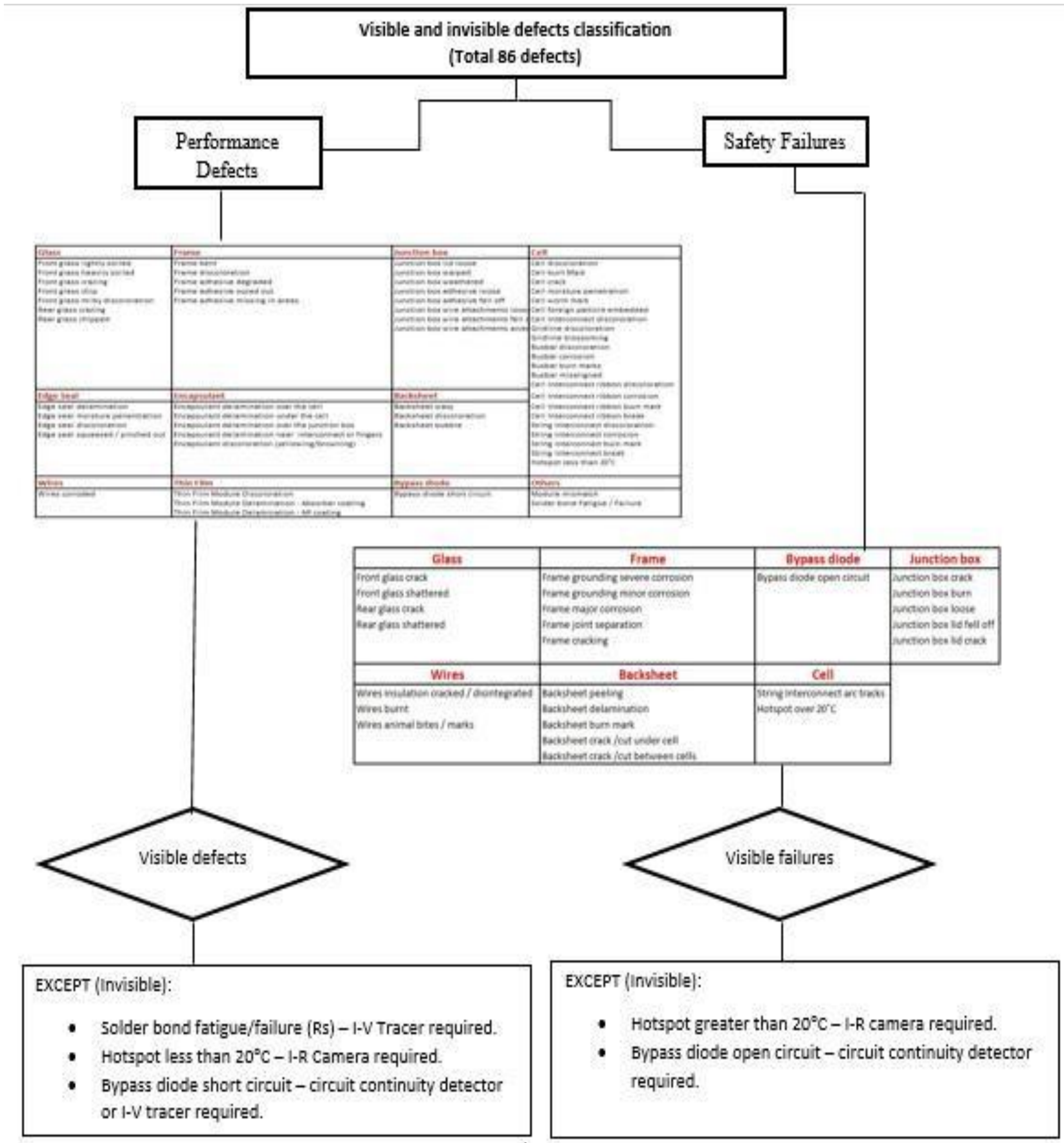


Figure 2: Visible and invisible defects classification [Performance defects and safety failures are listed elsewhere, [4]]

Janakeeraman et.al [27] analyzed the IV data collected from 8 different PV power plants in Arizona to identify the IV parameters which are responsible for degradation of power and correlated them with the defects/failures found in PV modules.

Umachandran et.al [12] correlated the visual defects found in power plants obtained from 5 different PV power plants in Arizona and New York with IV parameters to identify the exact defect/failure which is liable for affecting the dominant IV parameter causing Pmax degradation. In this thesis we try to classify these defects/failures as visible (to the naked eye) or invisible (equipment need to find presence/absence of a particular defect). Invisible defects are assigned with a high number for detectability as they are not visible to the naked eye and the risk posed by such defects could be dangerous as it is easy to overlook them when they might be causing high losses in performance. Such defects have to be detected using sophisticated equipment such as I-V curve tracer, I-R camera or circuit continuity detectors. Solder bond failures was one of the invisible defects which contributes to huge losses in performance and needs to be detected using the I-V tracer. Visible defects on the other hand are given a low number for detectability as they do not require sophisticated equipment for detection and are visible to the naked eye. In this thesis, a classification table classifying all the defects observed in PV modules as visible and invisible, method to detect invisible defects and the corresponding performance parameters affected was created which is shown below.

1.3.2 Performance parameter primarily expected to be affected by each defect

Power = Isc x Voc x FF

(VI=Visual; IV=I-V curve; IR=IR imaging; CC=Circuit Continuity; UV=UV fluorescence); Yes (Y) = Affected; Yes/No (Y/N) = May be affected

Table 1: Defect Affecting Performance Parameters

Defect #	Defect – Performance Defect	Detection Method VI/IV/IR/CC	Parameter Affected: Isc	Parameter Affected: Voc	Parameter Affected: FF
1	Front glass lightly soiled	VI	Y		
2	Front glass heavily soiled	VI	Y		
3	Front glass crazing	VI	Y		
4	Front glass chip	VI	Y/N		
5	Front glass milky discoloration	VI	Y		
6	Rear glass crazing	VI			Y/N
7	Rear glass chipped	VI	Y/N		
8	Edge seal delamination	VI			Y
9	Edge seal moisture penetration	VI			Y
10	Edge seal discoloration	VI			Y/N
11	Edge seal squeezed / pinched out	VI			Y/N
12	Frame bent	VI	Y/N		
13	Frame discoloration	VI			Y/N
14	Frame adhesive degraded	VI			Y/N
15	Frame adhesive oozed out	VI			Y/N
16	Frame adhesive missing in areas	VI			Y/N
17	Bypass diode short circuit (Equipment needed)	IV/IR/CC		Y	Y
18	Junction box lid loose	VI			Y/N
19	Junction box lid crack	VI			Y/N
20	Junction box warped	VI			Y/N

21	Junction box weathered	VI			Y/N
22	Junction box adhesive loose	VI			Y/N
23	Junction box adhesive fell off	VI			Y/N
24	Junction box wire attachments loose	VI			Y
25	Junction box wire attachments fell off	VI	Y/N	Y/N	Y/N
26	Junction box wire attachments arced	VI	Y/N	Y/N	Y/N
27	Wires corroded	VI			Y/N
28	Backsheet wavy	VI	Y/N		Y/N
29	Backsheet discoloration	VI	Y/N		
30	Backsheet bubble	VI	Y/N		Y/N
31	Gridline discoloration	VI	Y/N		Y
32	Gridline blossoming	VI	Y/N		Y
33	Busbar discoloration	VI	Y/N		Y
34	Busbar corrosion	VI	Y/N		Y
35	Busbar burn marks	VI	Y/N	Y	Y
36	Busbar misaligned	VI			Y
37	Cell Interconnect ribbon discoloration	VI	Y/N		Y
38	Cell Interconnect ribbon corrosion	VI	Y/N		Y
39	Cell Interconnect ribbon burn mark	VI	Y/N	Y	Y
40	Cell Interconnect ribbon break	VI	Y	Y	Y
41	String Interconnect discoloration	VI	Y/N		Y
42	String Interconnect corrosion	VI	Y/N		Y

43	String Interconnect burn mark	VI	Y/N	Y	Y
44	String Interconnect break	VI	Y	Y	Y
45	Cell discoloration	VI	Y/N		Y
46	Cell burn Mark	VI		Y/N	Y
47	Cell chipping/crack	VI	Y/N	Y/N	
48	Cell moisture penetration	VI	Y/N	Y/N	Y
49	Cell worm mark (Snail Tracks)	VI	Y	Y	Y
50	Cell foreign particle embedded	VI	Y/N		
51	Interconnect discoloration	VI	Y/N		Y
52	Solder bond Fatigue / Failure (Equipment needed)	IV/IR			Y
53	Hotspot less than 20˚C (Equipment needed)	IR			Y
54	Encapsulant delamination over the cell	VI/UV	Y	Y	Y
55	Encapsulant delamination under the cell	VI			Y
56	Encapsulant delamination over the junction box	VI	Y	Y	Y
57	Encaps. delamination near interconnect or fingers	VI	Y		Y
58	Encapsulant discoloration (yellowing/browning)	VI	Y		
59	Thin Film Module Discoloration	VI	Y/N		Y
60	Thin Film Module Delam. - Absorber/TCO layer	VI	Y	Y	Y
61	Thin Film Module Delamination - AR coating	VI	Y		
62	Module mismatch	VI	Y		
	Defect - Safety Failures				

63	Front glass crack	VI	Y	Y	Y
64	Front glass shattered	VI	Y	Y	Y
65	Rear glass crack	VI	Y	Y	Y
66	Rear glass shattered	VI	Y	Y	Y
67	Frame grounding severe corrosion	VI			N
68	Frame grounding minor corrosion	VI			N
69	Frame major corrosion	VI			N
70	Frame joint separation	VI			N
71	Frame cracking	VI	Y/N		N
72	Bypass diode open circuit (Equipment needed)	IR/CC	Y/N		Y/N
73	Junction box crack	VI	Y/N		Y
74	Junction box burn	VI	Y/N		Y
75	Junction box loose	VI	Y/N		Y
76	Junction box lid fell off	VI	Y/N		Y
77	Wires insulation cracked / disintegrated	VI			Y
78	Wires burnt	VI	Y/N		Y
79	Wires animal bites / marks	VI			Y
80	Backsheet peeling	VI	Y	Y	Y
81	Backsheet delamination	VI	Y	Y	Y
82	Backsheet burn mark	VI	Y	Y	Y
83	Backsheet crack /cut under cell	VI			Y
84	Backsheet crack /cut between cells	VI			Y
85	String Interconnect arc tracks	VI	Y/N		Y

86	Hotspot over 20˚C (Equipment needed)	IR	Y	Y	Y

Figure 3: Visible and invisible defects classification [Performance defects and safety failures are listed elsewhere, [4]]

1.3.3 Comprehensive Analysis of Power Plants:

Identifying the potential defects/failures that could occur in the field provides an insight for the manufacturers. Using the defects database generated in this thesis, the industry will be able to quantify safety and performance risks for these defects so that appropriate accelerated tests to mitigate the effect of that particular defect can be developed.

1.3.4 Risk Priority Number:

In part 1 of this project, the aim is to categorically determine the RPN for defects occurring In 10 power plants around USA based on the occurrence, detectability and severity table developed by Shrestha et.al [13] for the PV industry. Each of these power plants belong to one of the 4 climatic conditions – Hot and Dry, Cold and Dry, Hot and Humid and Temperate. For each of these power plants, every defect occurring in each of these power plants has been assigned with a RPN number. Shrestha et.al [13] defines RPN, risk priority number, as one of the approaches for quantification of the criticality of the failure mode as indicated in IEC 60812 2006-01 Standard [8] and is given by

$$RPN = S * O * D$$

Where: S means Severity which is a measure of how strongly a system or a consumer is affected due to the effect of the defect present.

O means Occurrence (or likelihood) which denotes how probable it is for the particular failure mode to occur for a predetermined time interval

D means Detection which is an estimate of how easily the defect or the failure mode can be identified before the failure reaches the customer. [13]

Using this equation as a formula, the program developed by Mathan et.al [4] calculates the RPN based on Severity, occurrence and detection. The Severity table proposed by Shrestha et.al [3] was modified by Mathan et.al [4] which has been used here. The occurrence and detection table developed by Shrestha et.al. [3] has been shown below.

Severity Ranking	Severity Criteria	Changes to the severity table
1	No Effect, Rd < 0.3%	No change
2	Insignificant, Rd approx to 0.3%	No change
3	Minor Cosmetic Defect, Rd < 0.5%	No change
4	Cosmetic defect with Rd < 0.6%	No change
5	Reduced performance, Rd < 0.8%	No change
6	Performance Loss approx to typical warranty, Rd approx to 1%	No change
7	Significant degradation, Rd approx to 1.5%	No change
8	Remote safety concerns, Rd < 1%	Rd > 1.5 & Rd <= 2 for performance defects | Bypass diode OC failure
9	Remote safety concerns, Rd < 2%	Rd > 2 for performance defects | Rd <= 2%
10	Safety Hazard, Catastrophic	Rd > 2% | 18 safety failures

Table 2: Severity table

Failure Mode Occurrence	Frequency CNF/1000	Ranking O
Remote: Failure is unlikely	<= 0.01 module per thousand per year	1
Low: Relatively few failures	0.1 module per thousand per year	2
	0.5 module per thousand per year	3
Moderate: Occasional failures	1 module per thousand per year	4
	2 module per thousand per year	5
	5 module per thousand per year	6
High: Repeated failures	10 module per thousand per year	7
	20 module per thousand per year	8
Very high: Failure is almost inevitable	50 module per thousand per year	9
	>= 100 module per thousand per year	10

Table 3: Occurence table

Ranking	Criteria: Likelihood	Detection
1	Monitoring System itself will detect the failure mode with warning 100%	Almost certain
2	Very high probability (most likely) of detection through visual inspection	Very high
3	50/50 probability (less likely) of detection through visual inspection	High
4	Very high probability (most likely) of detection using conventional handheld tool e.g. IR, Megger	Moderately high
5	50/50 probability (less likely) of detection using conventional handheld tool e.g. IR, Megger	Moderate
6	Very high probability (most likely) of detection using nonconventional handheld tool e.g. diode/line checker	Low
7	50/50 probability (less likely) of detection using nonconventional handheld tool e.g. diode/line checker	Very low
8	Very high probability (most likely) of detection using	Extremely
	performance measurement equipment e.g. IV tracer	Low

Table 4: Detection table

1.3.5 MATLAB Program input data:

The generation of RPN for 15 power plants is done using the MATLAB program developed by Mathan et.al [4] and by using two forms as spreadsheet as the input: One is the defects spreadsheet (IV Data) and other one is the degradation rate spreadsheet (VI). Both these spreadsheets have to be in the exact format as shown below in order for it to run in the MATLAB program.

Module	Rated Isc	Rated Voc	Rated Imax	Rated Vmax	Rated FF	Rated Pmax	Measured Isc	Measured Voc	Measured Imax	Measured Vmax	Measured FF	Measured Pmax	Age
C2-S1-T1	3.87	42.10	3.56	33.70	73.63	120.00	3.65	41.26	3.13	33.84	70.30	105.77	17.79
C2-S1-T2	3.87	42.10	3.56	33.70	73.63	120.00	3.87	41.38	3.22	35.28	70.79	113.44	17.79
C2-S1-T3	3.87	42.10	3.56	33.70	73.63	120.00	3.71	41.33	3.31	33.51	72.48	111.04	17.79
C2-S1-T4	3.87	42.10	3.56	33.70	73.63	120.00	3.71	40.54	3.35	32.46	72.30	108.67	17.79
C2-S1-T5	3.87	42.10	3.56	33.70	73.63	120.00	3.70	41.07	3.33	33.31	73.08	111.00	17.79
C2-S1-T6	3.87	42.10	3.56	33.70	73.63	120.00	3.68	41.05	3.31	32.91	72.07	108.89	17.79
C2-S2-T1	3.87	42.10	3.56	33.70	73.63	120.00	3.75	41.05	3.36	33.07	72.12	111.16	17.79

Figure 4: I-V data format

The Degradation rate spreadsheet needs to be saved as IV data and the Defects spreadsheet needs to be saved as VI. Saving these two spreadsheets by any other name will result is the program not running. Once the data has been inputted in the form of 2 spreadsheets, the global RPN program produces the RPN number for every defect. It also provides us with an additional 5 graphs which helps us determine other characteristics related to RPN.

Below is the RPN plot generated for a particular power plant and based on this we generate RPN for 15 power plants. In this thesis, we consider the global RPN plots shown below:

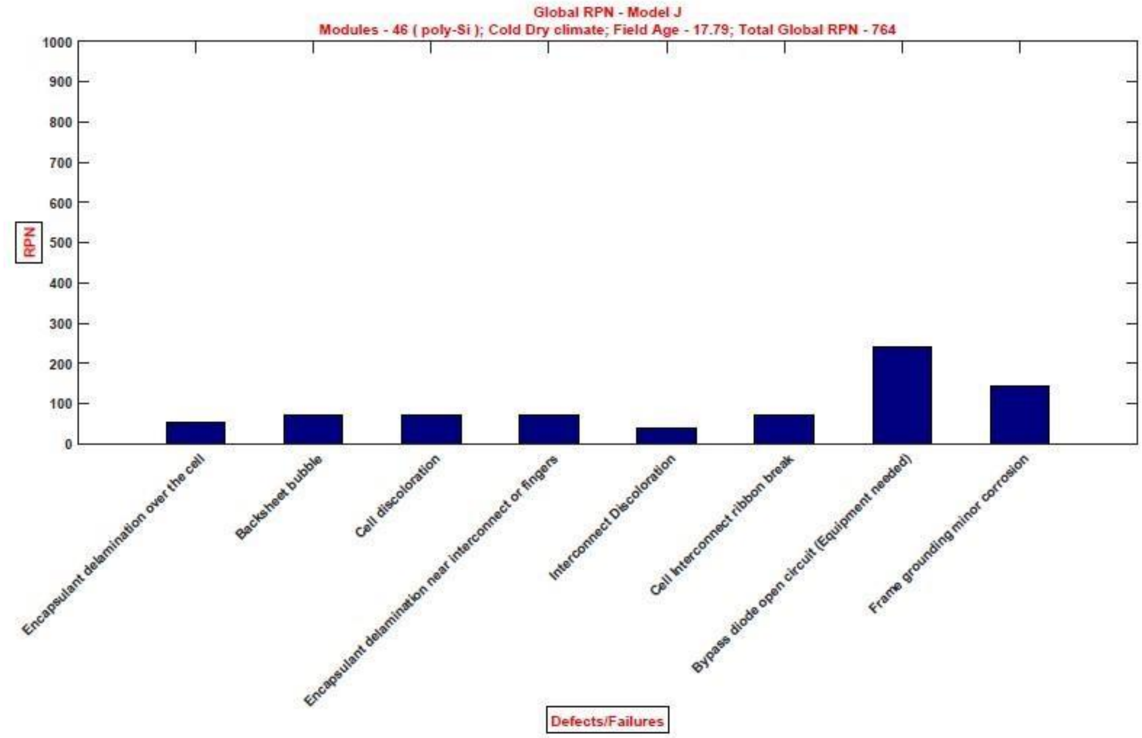


Figure 5: Global RPN for defects in MODEL J

Figure 3: Global RPN graph for each defect found in that power plant

1.3.8 Method to Detect the Dominant Defect in Each Power Plant

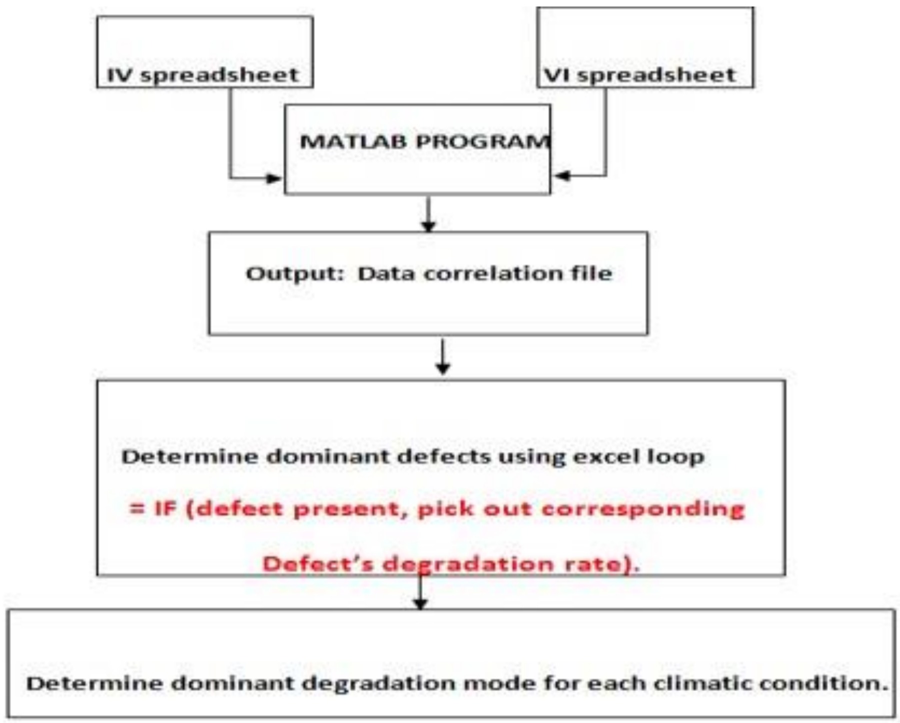


Figure 6: Method to detect dominant performance parameter

1.3.9 Generic dominant defects pie chart:

The usual pie chart's which are published in the industry contain dominant defects found in each climatic condition. However, these pie charts do not give an idea of the level of risk associated to these dominant defects. In this part of the thesis, an attempt at quantifying the level of risk associated to these defects found in different climatic conditions by assigning a risk priority number to the dominant defects (figure (14) and figure (15) in the results and discussion section). This way we can quantify the risk associated to the dominant defect. Below we can see two such pie charts, figure 7 and figure 8 published in [28] shows the dominant defects calculated in percentage as compared to the total number of failures.

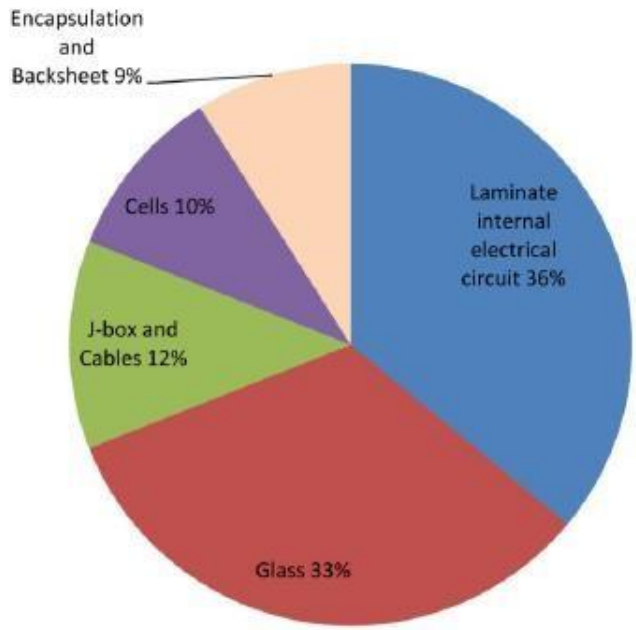


Figure 7: Generic pie chart showing percentage of each defect [28]

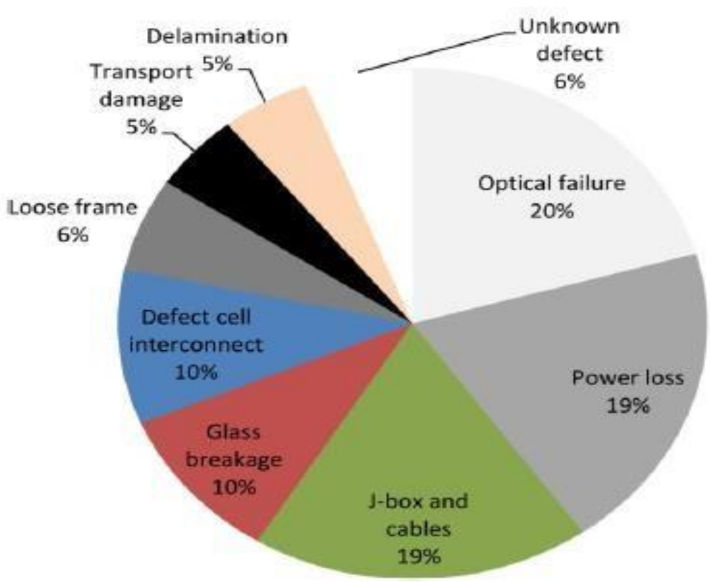


Figure 8: Generic dominant defect flowchart based on customer complaints [28]

1.4 RESULTS AND DISCUSSION

1.4.1 Degradation vs. Technology vs. Climate

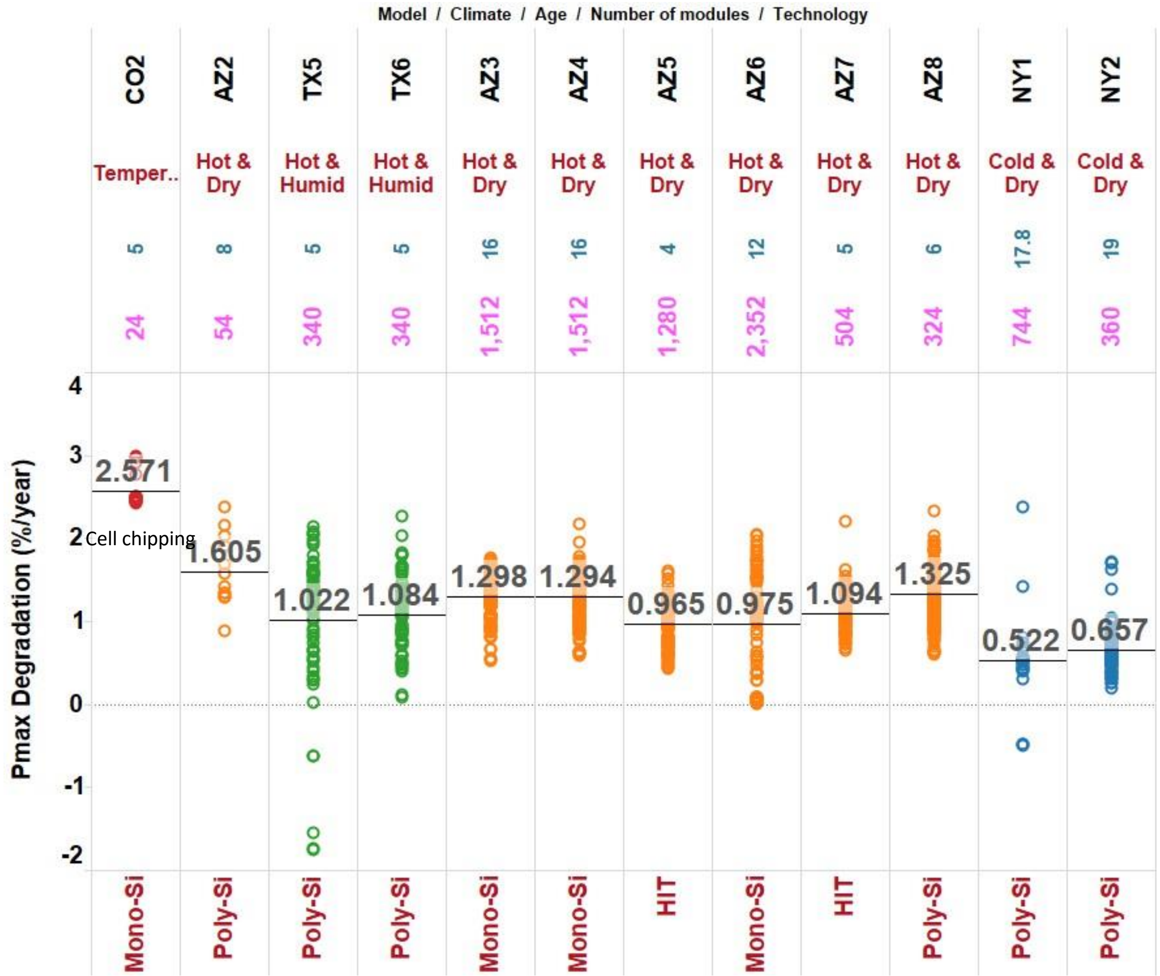


Figure 9: Classification of defects across different climatic condition

The degradation rate of the crystalline silicon modules appears to be the highest if visual chipping occurs in the cells probably due to repeated thermal expansion/contraction of the cell materials and stiffening of packaging materials in the cold weather.

The degradation rate of the poly-Si modules appears to be the lowest probably due to low field exposure (5 years) without any additional loss due to any encapsulant browning.

In general, based on this plot, it can be concluded that the crystalline silicon modules degrade in the following order: hot-dry > hot-humid >> cold-dry.

1.4.3 Degradation vs. Defect (for C-Si technology) vs. Climate

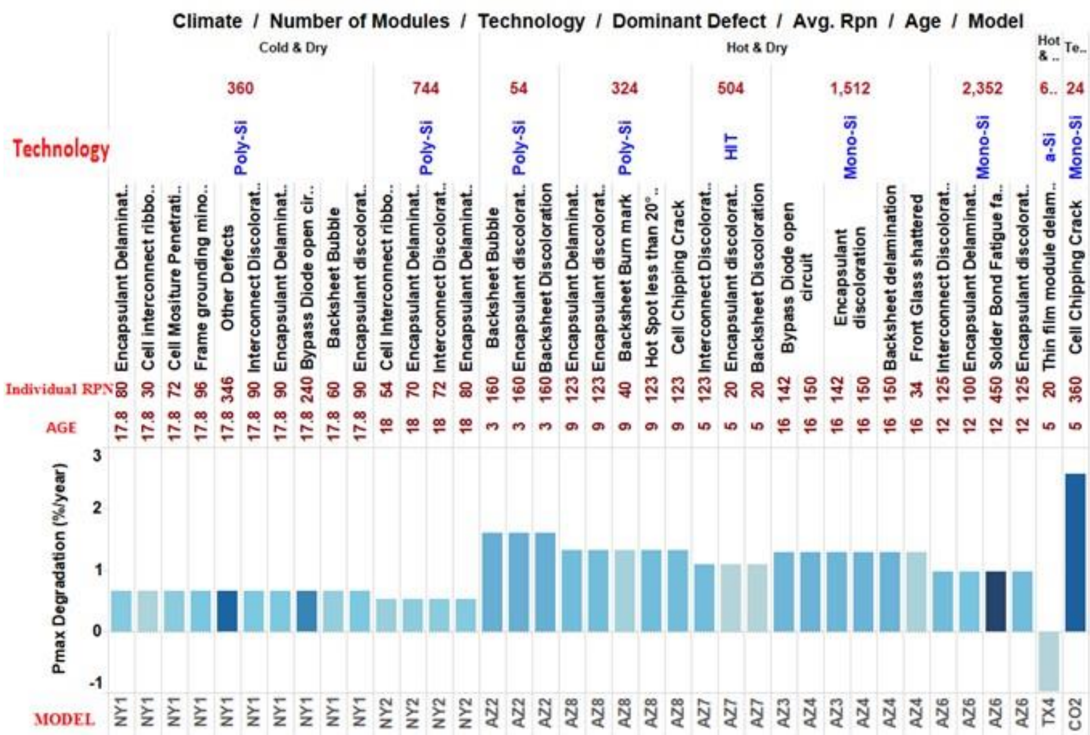


Figure 10: Classification of defects with RPN color coordinated

The graph above gives us the different defects in the different climatic conditions and the defects found in each climate. Additionally the risk priority numbers are color coded where the defect with the highest RPN is dark blue and the defect with the lowest RPN is light blue in color.

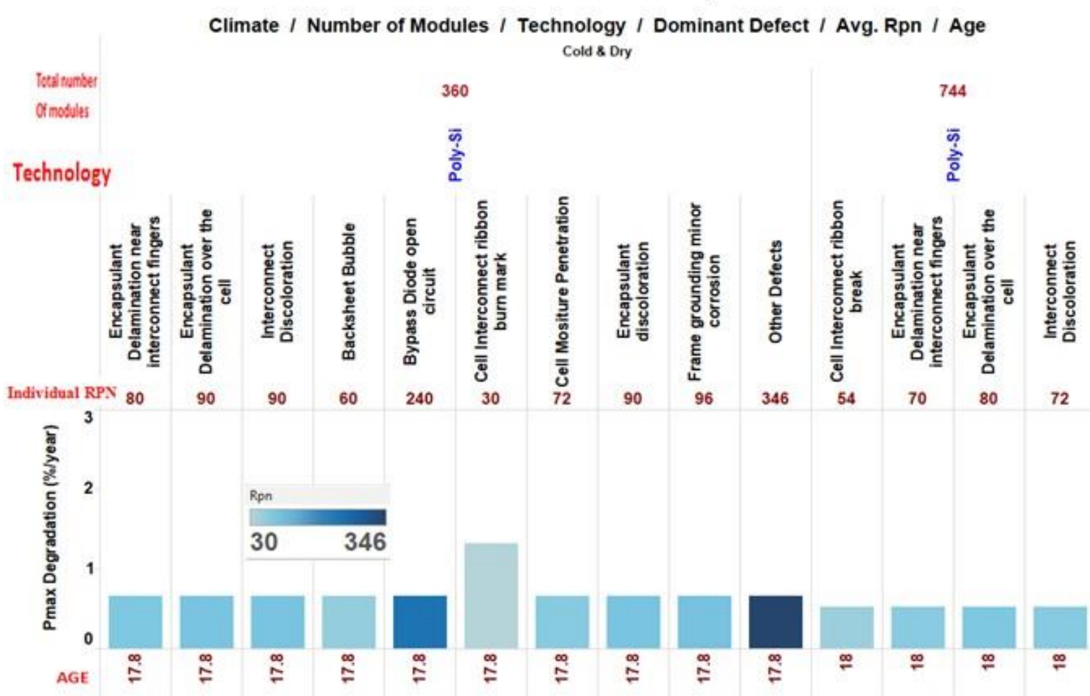
From the above graph it can be observed that cell chipping and solder bond degradation have very high Risk priority numbers.

Another major conclusion from this graph would be that the RPN of defects found in HotDry weather condition is higher than the RPN for Cold-Dry and Hot-Humid. Also Hot-Dry weather condition has a much wider variety of defects as compared to other climatic conditions.

From this graph we can infer the order of RPN for different climatic conditions to be: Hot-Dry > Cold-Dry >> Hot- Humid

The Hot-Humid climatic condition has less number of defects because the plants are only 5 years old.

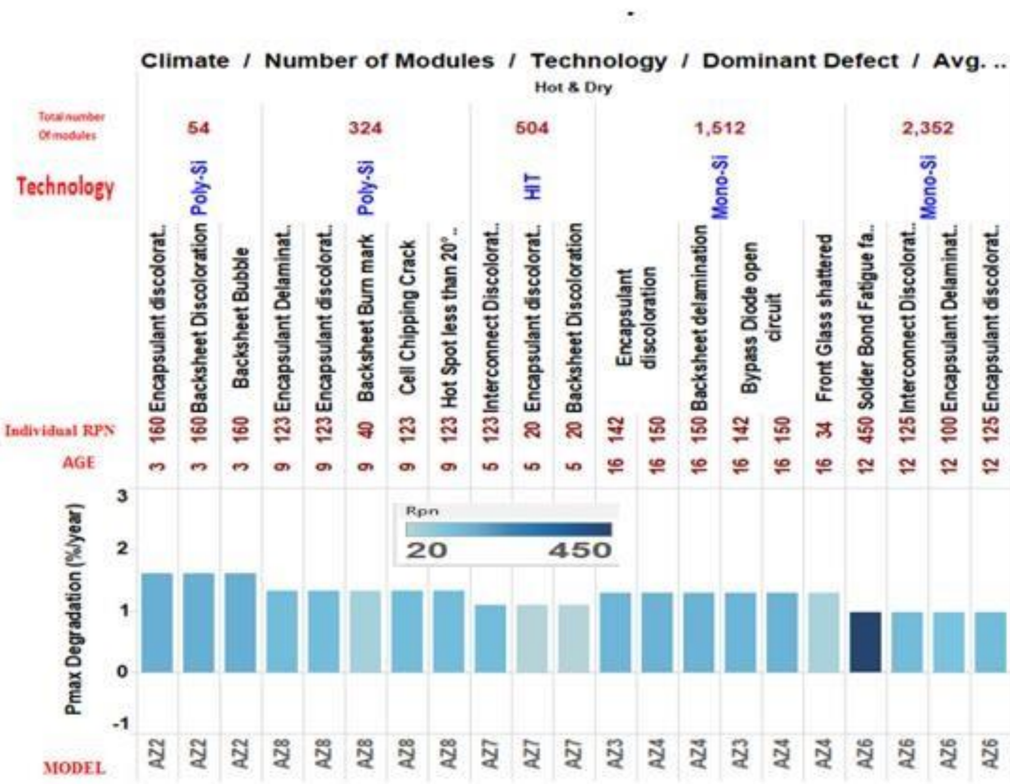
1.4.3.1 Degradation vs. Defect (for C-Si technology) vs. Cold and Dry Climate



In both the power plants analyzed in this climatic condition, we can see that interconnect discoloration and encapsulant delamination is observed to be present.

We can also see a high RPN for other defects for NY2 as there were 6-8 defects with low RPN values which were not occurring in any other power plant. It was determined that these are not the dominant defects due to the low RPN they possess and were grouped together as other defects.

1.4.3.2 Degradation vs. Defect (for C-Si technology) vs. Hot and Dry Climate



Thousands of modules in the hot dry climatic condition was analyzed and larger number of defects were observed as compared to the other climatic conditions.

From the above graph, it is clearly visible that solder bond fatigue failure has the highest RPN. Encapsulant discoloration seem to be happening in almost every power plant in the hot dry climatic condition.

1.4.4 Degradation of All Technologies vs climatic conditions

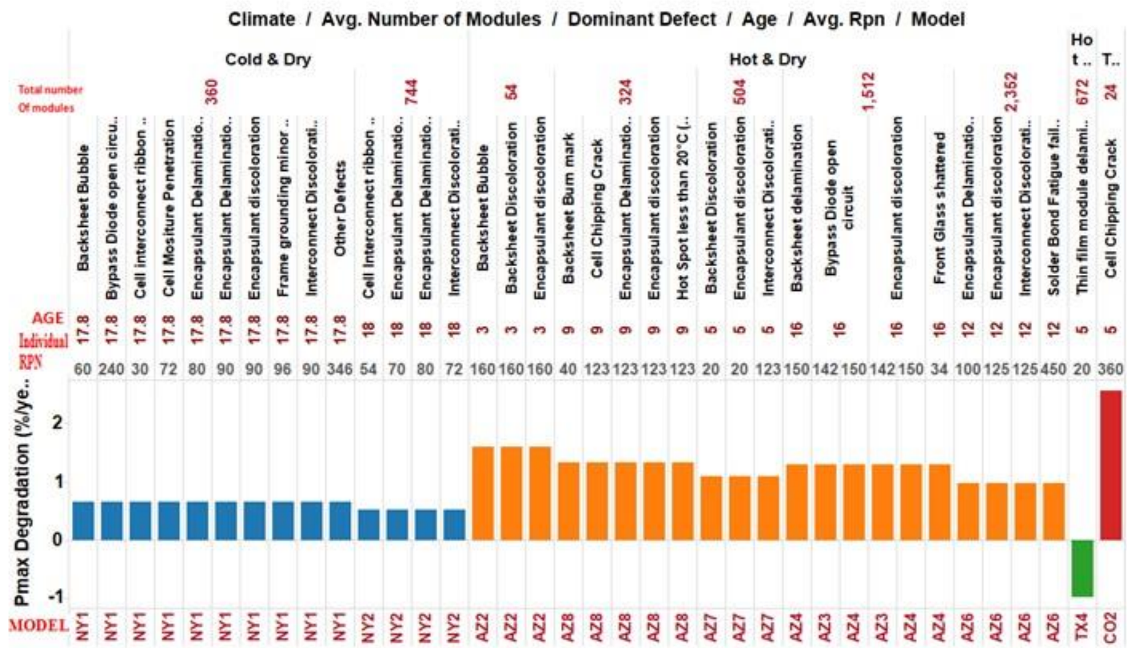


Figure 11: Defects color coordinated for different regions with corresponding RPN/age

This graph shows us the number of defects observed in each weather condition and the RPN of each defect and the ages in which these defects are found in that particular power plant.

This graph was plotted for 4 different climatic conditions (color coded) and represent the total degradation happening in each power plant along with the level of risk of each defect which is being provided by the RPN.

1.4.6 Hot and Dry – Dominant Defects

14 models evaluated; 7358 modules; 03-19 years age range

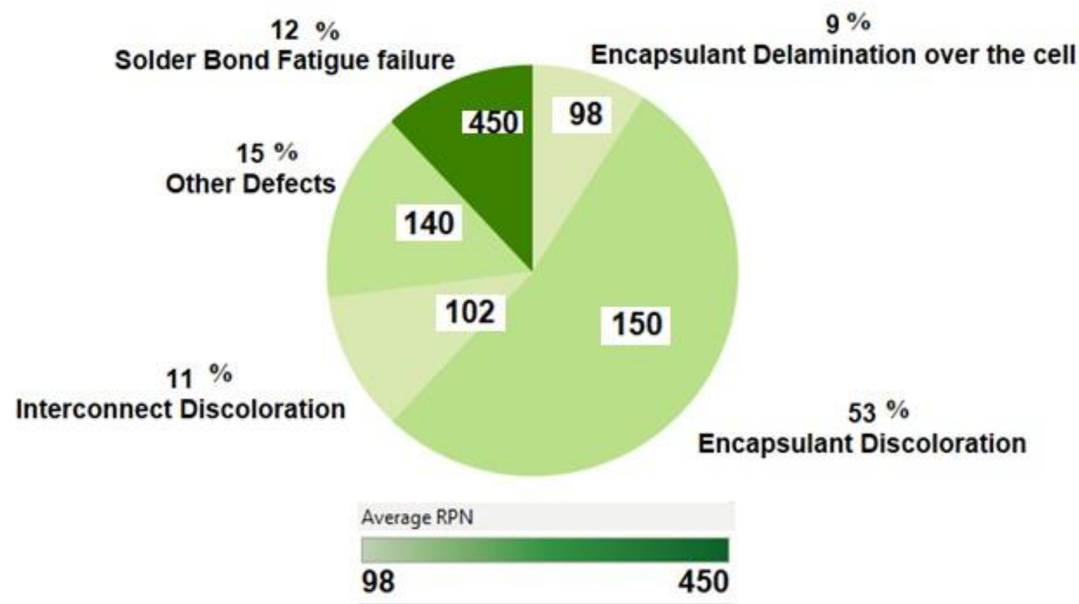


Figure 12: Dominant defect found in hot and dry climatic condition (7358 modules; 14 models; 03-19 years age range)

We can conclude from the above graph we can clearly see that the most dominant defect observed in Hot-Dry weather condition is Encapsulant discoloration and solder bond fatigue failure shown along with the level of risk due to these defects is shown in the above graph.

1.4.7 Cold and Dry – Dominant Defects

3 models evaluated; 1128 modules; 05-19 years age range

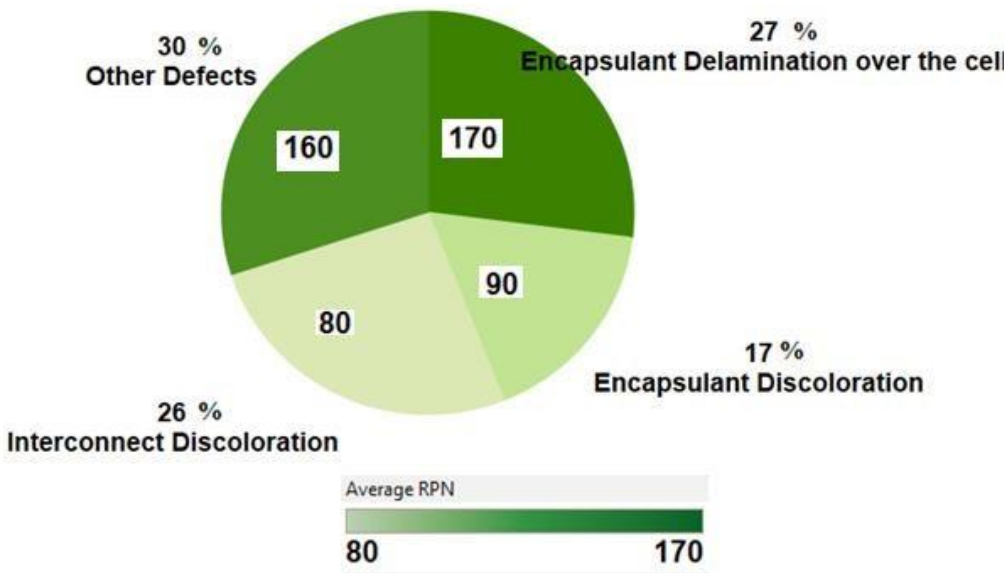


Figure 13: Dominant defects found in cold and dry climatic conditions

In cold and dry weather condition, the most dominant defect seems to be Encapsulant delamination over the cell and interconnect discoloration along with the associated level of risk due to these defects is given using the RPN technique. In the cold and dry weather condition, a wide range of defects with small RPN values are observed.

1.5 CONCLUSION

In the first part, a detailed analysis on the performance or financial risk related to each defect found in multiple PV power plants across various climatic regions of the USA is presented by assigning a risk priority number (RPN). In this analysis it is determined that the RPN for each plant is dictated by the technology type (crystalline silicon or thin-film), climate and age. The PV modules aging between 3 and 19 years in four different climates of hot-dry, hot-humid, cold-dry and temperate are investigated in this study. Using an automated RPN program developed in a previous work at ASU-PRL and with the vast amount data collected by ASU-PRL over several years, it was possible to calculate the RPN for multiple power plants across varied weather conditions in the USA. The automated MATLAB based RPN program also produces a data correlation file which gives us the rate of degradation of each performance parameter and by using this information one can pinpoint the dominant performance parameters (Voc, Isc and FF) affected by each defect.

This study performed the defect correlation only for one parameter, power (Pmax). Overall, based on the RPN analysis, the Pmax parameter is determined to be affected by two dominant defects of encapsulant discoloration and solder bond defects across multiple power plants in multiple climatic conditions. In some specific power plants, the defects of cell chipping and bypass diode failure under open-circuit condition are determined to have very high RPN values as compared to other defects. This study recommends to extend this correlation analysis for the other performance parameters of short-circuit current (Isc), open-circuit voltage (Voc) and fill factor (FF).

PART 2: DEGRADATION ANALYSIS OF PV POWER PLANTS

2.1 INTRODUCTION

Linearity in degradation is analyzed using 2 methods, namely, the I-V method and kWh method. The I-V method involves going to the plant in person along with several equipment (such as I-V curve tracer, thermocouples, reference cells, etc.) and calculating degradation using the data collected from the mean median and worst performing strings within a 95% confidence interval. In the I-V method, the annual Pmax degradation of 7538 crystalline silicon modules of different ages present across 6 power plants in the hot and dry weather condition is analyzed. The kWh method involves the statistical analysis performed on the metered raw kWh data obtained from the inverter data logger which can be accessed remotely from any location. This data consists of signal and noise components. Exponential smoothers such as Winters' method which is used for data which show seasonal variations. These smoothers remove the noise from the data by taking the average of the current and previous observations. Further, analysis of the noise (residual plot) will determine whether the noise is random or not based on 4 conditions. If the 4 conditions are satisfied then the noise is random and the data can be trusted. We make an assumption of linear degradation and model the data to calculate degradation. Accurate values of degradation seems to imply that our initial assumption that degradation is linear is correct for these two particular power plants. Using these two methods and evaluation of thousands of modules, we could come to a conclusion on the linearity of degradation in the hot dry condition.

2.1.1 Background:

In order to model the kWh data we obtain from the inverter, we need to first determine that the components in the balance of system do not degrade because if they do degrade then it could be contributing to the PV module degradation and we need to consider other degradations in modelling kWh degradation. Hence we analyze different components in the balance of system whether they fail or degrade. The components of the balance of system usually fail at the end of their service life and do not degrade. Hence we statistically model for the module degradation alone.

2.1.1.1 Balance of system and its components:

The balance of system encompasses all components of a photovoltaic system other than the PV panels. This includes wiring, switches, mounting system, inverter and battery. In order to model the kWh data we obtain from the inverter, we need to first determine that the components in the balance of system do not degrade because if they do degrade then it could be contributing the PV module degradation and we need to consider other degradations in modelling kWh degradation. Hence we analyze different components in the balance of system whether they fail or degrade.

- Inverter: Does not degrade over time. Performs throughout service life and fails.
- Mounting System: The single axis trackers being considered in the analysis here does not have any degradation losses of PV module due to mounting. Neither is there any degradation due to batteries as these modules are connected to the grid.

Since almost all the components in the balance of system fail and none of them degrade, we attribute the trends observed in the kWh graphing to be due to the module degradation only.

Hence we model the data for variations in module degradation. This is done using the winter's method in MINITAB.

2.1.2 Statement of problem:

Reason for using statistical technique's in data processing:

The data obtained by ASU-PRL is collected every 15 minutes and spans over 8 years of module's operation. In order to streamline the data processing and do it in a shorter time and a highly automated format with minimal manual filtration of outliers, we need to statistically model the data using time series techniques such as winter's method. The goal of this part of the thesis is to determine if degradation in the hot dry climatic condition is linear or nonlinear. We try to answer the question of linearity based on 2 established methods in the industry.

2.1.3 Objective

The degradation rate is a key parameter used by the PV module manufacturers to determine their warranty period and the system owners to predict the energy production and calculate the levelized cost of energy (LCOE). The PV industry typically utilizes three different methods to determine the degradation rate and they are: I-V method, performance ratio (PR) method and performance index (PI) method. The I-V method is ideal but it is a labor and cost intensive method. Also, this method requires complete shutdown of the power plant during I-V measurements. The PR method accounts for

YOY (year-over-year) insolation variation measurements on a daily, hourly and monthly basis; however, this method requires insolation data which is accurate from a ground mounted weather station. The PI method accounts for all sorts of YOY variations including insolation, temperature, soiling, angle of incidence, BOS losses etc.; however, again, this method requires accurate weather data. This thesis focuses on a fourth method called "metered kWh" method. This method does not require any weather data and all it requires is the metered kWh data. Only a select few research groups have explored this method as the degradation rates determined by this method are often inaccurate due to large number of outliers caused by variations in the environmental conditions including insolation and in the installation conditions including shading. In this thesis, we use this method to determine linearity and also the accurate degradation of power plants.

2.2 LITERATURE REVIEW:

The time series data which we model in this thesis consists of both cyclic patterns and seasonal patterns and such data cannot be successfully modeled using basic polynomial models. Several approaches are available for the analysis of such data. In this chapter we will discuss exponential smoothing techniques that can be used in modeling seasonal time series. This thesis focuses mostly on the Winters' method introduced by Holt [1957] and Winters' [1960], where a seasonal adjustment is performed to the fitted linear trend model as described in "Introduction to Time Series analysis and forecasting" (Douglas C. Montgomery, Cheryl L.Jennings and Murat Kulahci, 2008) [26]. Once the trend data is modelled regression analysis is performed on the data. The hypothesis test for significance of regression is performed to determine whether out modelled data represents linear degradation.

2.3 METHODOLOGY:

2.3.1.1 Process Flowchart

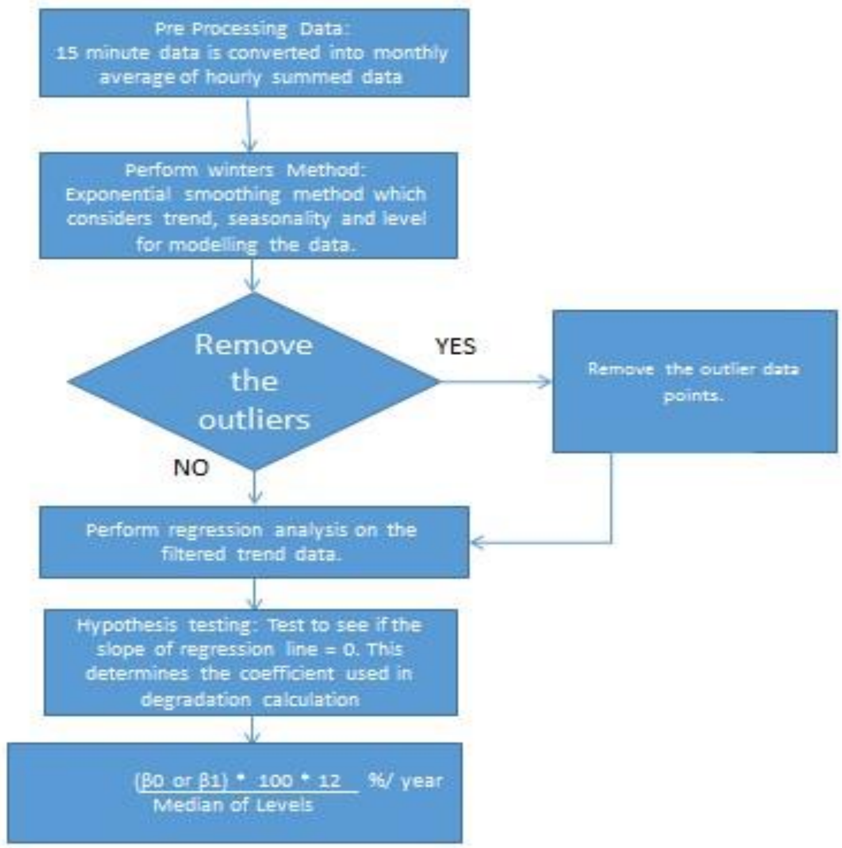


Figure 14: Process flowchart for statistical time series analysis

2.3.1.2 Preprocessing of data:

- The production of energy by the module is recorded by the inverter data logger. The data we get is in the CSV format and is obtained in the form of a text file.

- This CSV file is converted into excel column format as shown below. This is done with the help of an excel tool called text to columns.
- The data obtained in the data logger records data for every 15 minutes throughout the operation of the module. The energy output is in the form of kW and kWh. For

  this thesis, the kWh data has been considered as we are only interested the hourly, monthly and yearly energy production.
- The 15 minute data obtained is converted into hourly energy using the filtration tool in excel. The hourly kWh data needs to be preprocessed using excel before statistical analysis (processing) can be done on the data.
- The converted hourly kWh data is further tweaked and converted into summed daily data where each day (each data point) is the summation of the data produced every 24 hours i.e. the hourly data. This is done with the help of an excel tool called the pivot table.
- The daily data obtained is finally converted into monthly data (one data point per month). This daily summed data for each day in a month is averaged for each month. This data is the daily summed data averaged for each month. Therefore we end up with 12 data points per month. The Graph for preprocessed kWh energy produced during the plants operating lifetime is shown below.

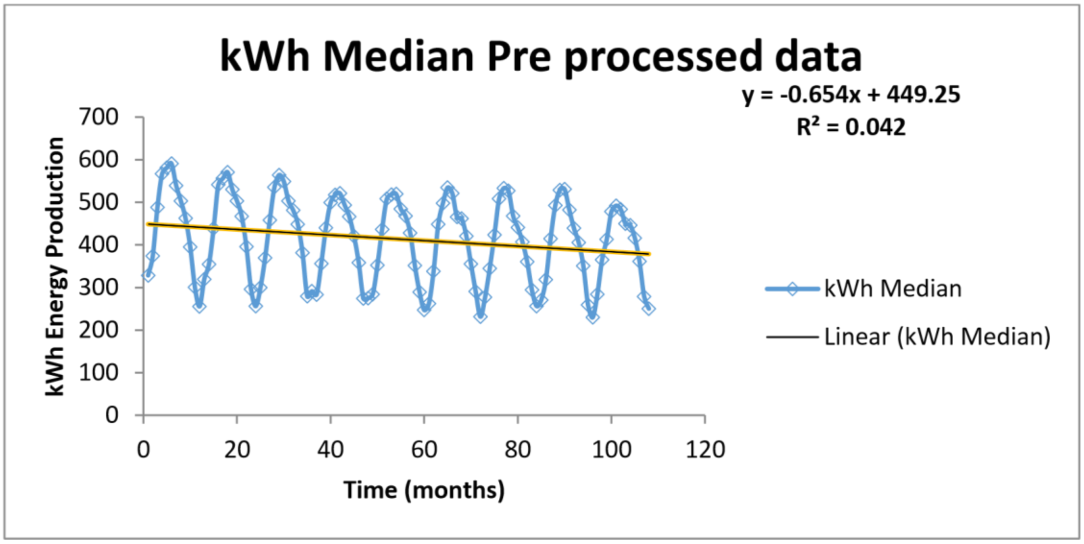


Figure 18: Graph of preprocessed data

2.3.1.3 Modelling data via time series methods:

The kWh data considered for the thesis is strongly affected by the seasonal variation. One of the most important parameters of module performance, which is, irradiance varies based on season. This directly alters the output data, i.e. kWh data and hence has to be modeled for seasonal variations.

2.3.1.4 Winter's Method:

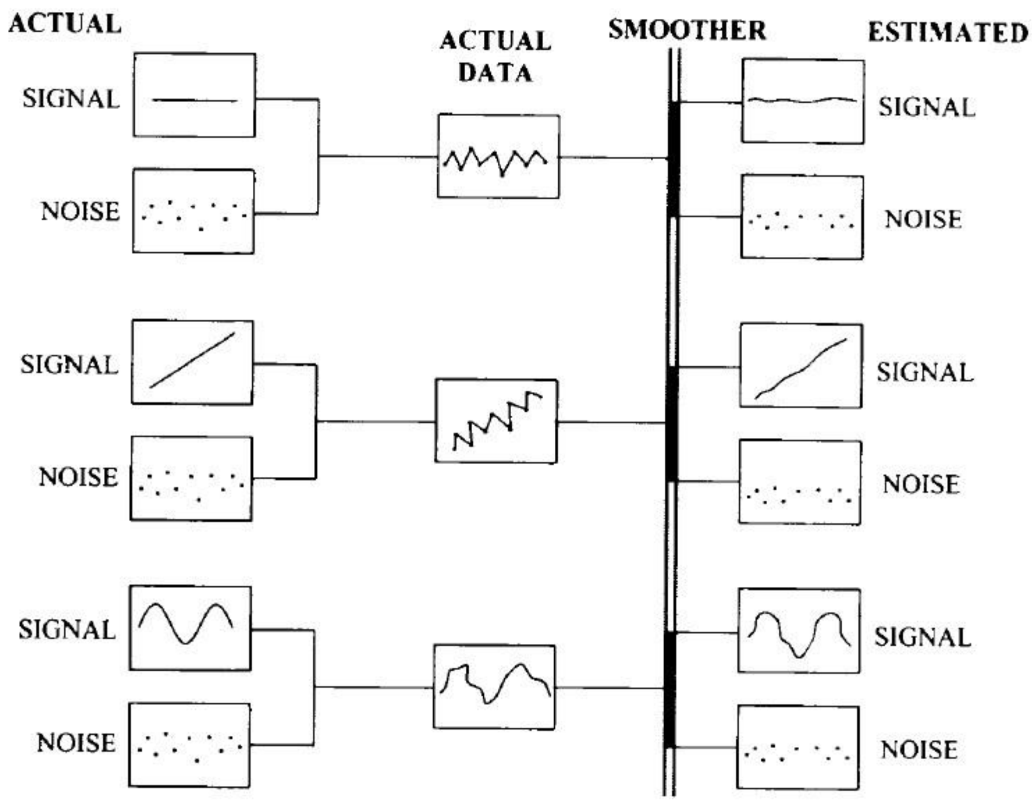


Figure 15: The process of smoothing a dataset [26]

The Holt-Winters method is made of three components used for modelling — one for the linear trend component L_t, and one for the seasonal component denoted by S_t and the error component which has a mean around zero and a constant variance as described in Montgomery et al. [26]. The Winters' method takes into consideration the level, seasonal and trend estimates into consideration and models the data. For both the power plants considered in this thesis, we focus more on the trend and level estimates produced by the winter's method.

2.3.1.5 Residual Analysis and smoothers:

Data = Signal + Noise

Residuals can be described as the difference between the observed value and the median of the previous values. There are various time series methods such as moving average, single exponential smoothing, double exponential smoothing, decomposition and Winters' method. Every data has two portions, one being the signal and the other being the noise. The residual can be thought of as the error and we analyze the residual four in one plot to check how efficiently the noise is separated from the signal. We choose the method which most efficiently separates the noise from the signal. For the data obtained at ASU-PRL, Winters' method seemed to remove the signal from the noise most effectively and we could model the signal using this method. This is determined by analyzing the residual analysis plots and proving noise random to see if they satisfy the following conditions:

- Constant variance
- Normal Distribution
- Mean around zero
- Autocorrelation (Does not apply to our data as you expect to see auto correlation in seasonal data).

These factors are analyzed using residual plot option where 4 different graphs are plotted in one which helps us determine if our data abides by the 3 conditions mentioned above.

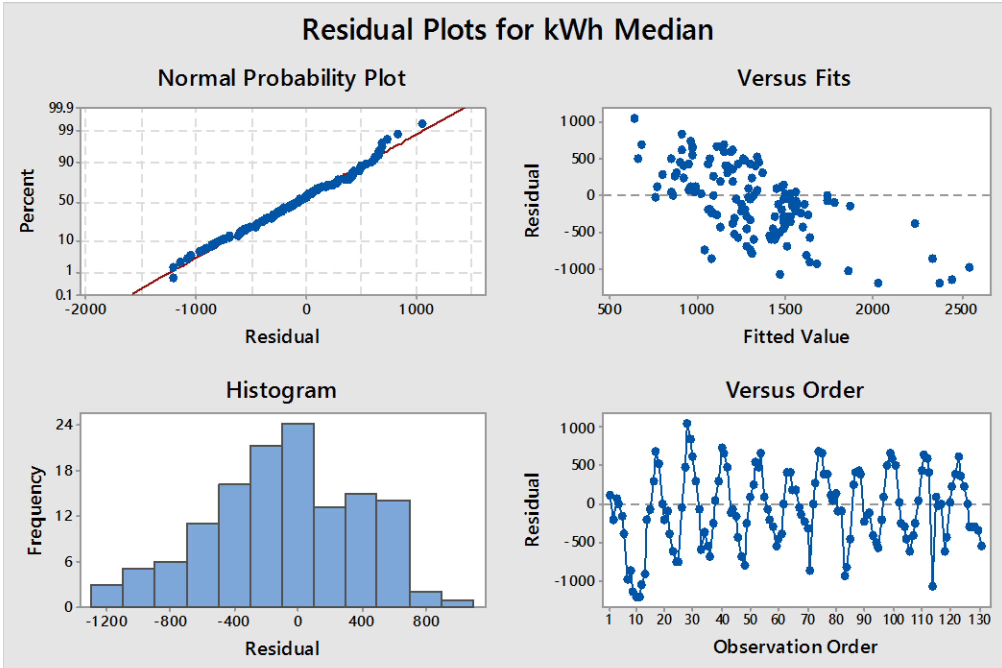


Figure 16: Analysis of the noise component of the data

- The frequency vs residual plot tells if our data is normally distributed or skewed.
- The percent vs residual plot tells us if our mean is distributed around zero or not.
- The residual vs fitted value plot tells us if our data has a constant variance or not.
- The residual vs observation graph tells us if the data is independent or auto correlated.

Based on analysis of these plot we can determine how well the noise is separated from the data. Hence analysis of residual plots becomes important.

2.3.1.6 Filtration of outliers in the trend data:

There are several types of adjustments in time series modelling. Two of the mostly used adjustments are the trend adjustments and seasonal adjustments. A time series which exhibits a trend is a non-stationary time series. We fit a linear model to our trend data using regression. We model only for the trend component and not for the seasonal component because trend component is overall trend observed in our data throughout the operation of the power plant where as seasonality varies in a cyclic pattern based on seasons. For example, the irradiance in hot and dry climate like Arizona will be high and for longer periods during the summer months than compared to the winters where the day light is typically shorter. We cannot fit a linear model to a cyclic pattern as it is already nonlinear. Hence our initial assumption that degradation is linear becomes invalid. The linear trend component gives the overall trend which our data follows. The trend models that are usually considered are the linear trend, in which the mean of Yt is expected to change linearly with time as described in Montgomery et.al [26] and is given by the equation

$$\mathrm{E(Yt) = \beta 0 + \beta 1t}$$

If this process was to be changed because of an extremely high value (outlier) in our data, then the trend data we use will react too slowly or too rapidly to changes. This will result in bad estimation of the trend data which we use to calculate the percentage degradation per year. As a result we would end up calculating the incorrect degradation rate. This is the reason why we need to remove the outliers we see in the trend data. The graph below shows the trend estimates obtained when winters method was applied for our data along with the outliers.

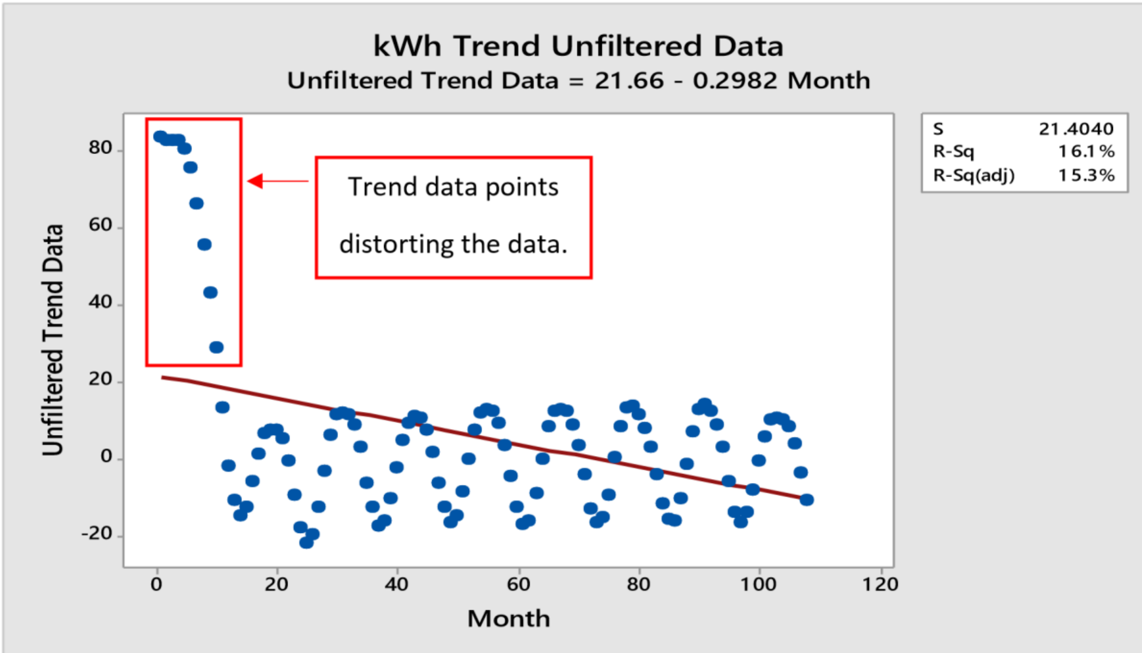


Figure 17: Unfiltered trend data

The initial points which distort our data were removed and regression analysis was performed on the new filtered trend data. It can also be observed that the linear regression equation obtained gives an extremely high coefficient value. When we use such a value for calculating degradation, the value which we obtain will be out of bounds and nowhere close to the correct value of % degradation per year. Further it also falsely leads us to believe that the degradation seems nonlinear.

2.3.1.7 Hypothesis testing:

Hypothesis testing is performed on the filtered trend data after removing outliers to see if the slope of the regression line is linear or not. This is of extreme importance because, if we find out that the slope = 0, then our coefficient used in the equation used for calculating percentage degradation per year changes from slope to y-intercept.

Hypothesis testing performed by hypothesizing if the slope value is 0 or not. This is done by assuming the null hypothesis $\mu_0 = 0$. This means we basically assume the slope of the regression line to be 0. Once we perform hypothesis testing, we look at the results and summary table to make a decision on the data that we have obtained. Value of interest is the p-value where p stands for probability. If the value is greater than 0.05 (i.e. 1-95% CI), then it means the slope of the regression line is zero and our assumption that degradation is linear is correct.

2.3.1.8 Regression analysis performed on the filtered trend data:

Accurate results of % degradation per year determine that our initial assumption that the degradation is linear is true. This is of extreme importance as the end goal of this part of the thesis is to determine the linearity in degradation. This is calculated by using the formula:

$$\frac{(\beta_0 \text{ or } \beta_1) * 100 * 12}{\text{Median of levels}} \quad \%/\text{year}$$

β_0 = y intercept β_1

= slope.

In our case, for the filtered trend data, the slope of the regression line determines the coefficient used in the calculation of degradation. We perform hypothesis testing on the slope of the regression line and hypothesize the slope to be 0, i.e., $\beta_0 = 0$. A high p-value indicates that our initial assumption that the slope is zero is correct. In such a case our y intercept β_1 used in the calculation of degradation. Degradation values for 2 power plants were observed to be within ±0.09 compared to the degradation calculated using the I-V method. Hence our initial assumption that the degradation is linear is true for these two power plants in the hot dry weather condition.

2.3.2 Linearity analysis using Pmax degradation in hot dry climatic condition

The IV database for 15 power plants is basically the data required to calculate performance degradation. This data was obtained through field testing. I-V curves were collected for individual modules for the best, median and worst strings of the whole plant. The performance of the string as a whole was initially tested and the best median and worst strings were chosen. From these selected strings individual modules were tested. The data was translated to standard test conditions: STC (25°C, 1000W/m^2).

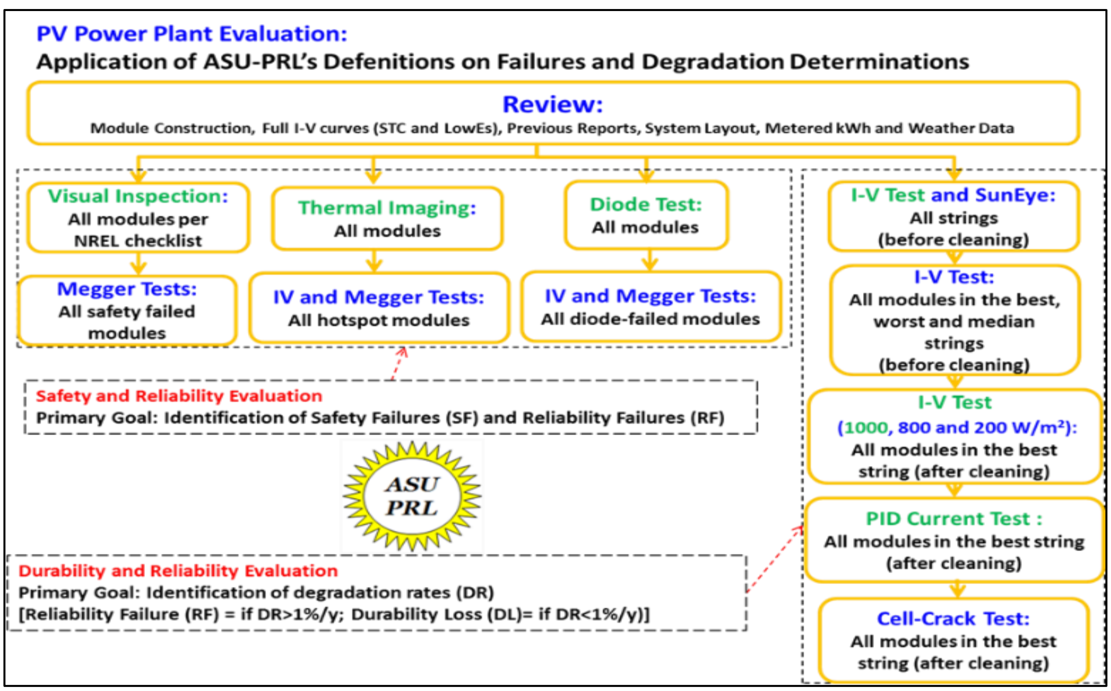


Figure 18: ASU-PRL power plant evaluation procedure

Visual Inspection data of these modules were obtained using visual inspection checklist modified by ASU-PRL based on the one developed by NREL [16]. Using the degradation data obtained for 6 such power plants in the hot-dry weather condition, a statistical determination on whether degradation is linear or nonlinear can be made. This will directly impact the leveled cost of Estimation (LCOE) for PV modules. We try to check if the Pmax degradation per year is linear or not based on the analysis of power plants having different ages. We plot the Pmax degradation rate per year (Y- axis) versus time (age – X axis). We try to see if the Pmax degradation rates of differently aged power plants fit the linear model.

2.4 RESULTS AND DISCUSSION:

2.4.1 MODEL CT

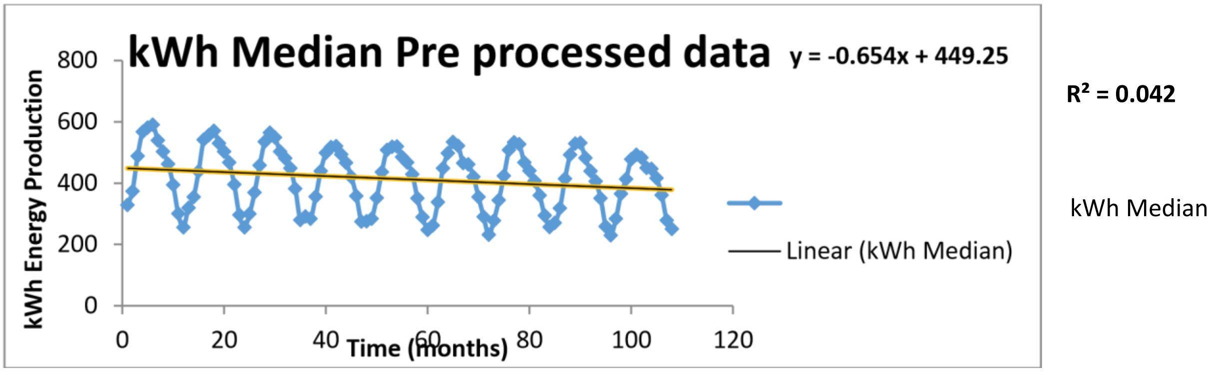


Figure 19: Preprocessed data for MODEL CJ

The Energy output is being recorded every 15 minutes by the Solar PV inverter. This energy produced is converted into hourly summation. The hourly summed energy is then averaged which gives us 12 data points for each year or 1 data point per each month. Graphing this data gives us the graph we see above and this is the preprocessed data which we use as input for statistical modelling based on time series methods.

2.4.1.1 Winters method on the preprocessed data:

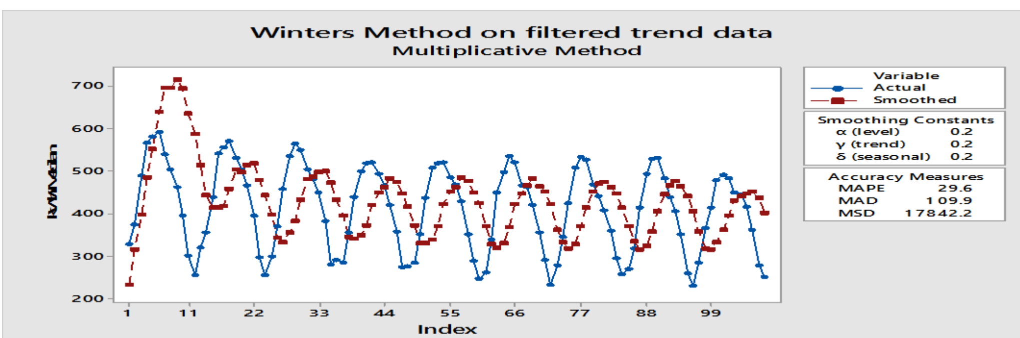


Figure 20: Winters method smoothed vs actual fit

The graph we see above shows us the difference between the actual and the smoothed data. The smoothed data is basically the exponential smoothing performed on the data

2.4.1.2 Residual analysis of the noise component

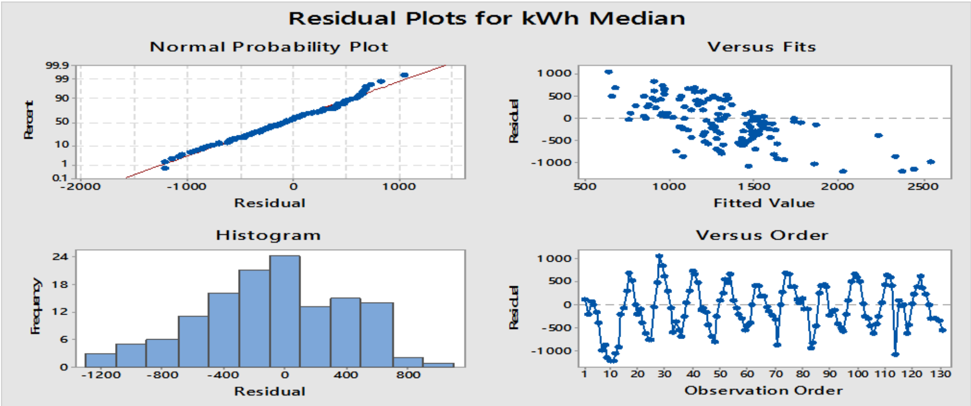


Figure 21: Residual (noise) analysis for MODEL AZ8

The residual plot analysis the noise and tells us how well the data was separated from the noise. Our residual plots seem to satisfy the conditions of normality. The noise is normally distributed and has constant variance. The data also seems to be auto correlated based on the residual vs observation order plot which is expected for a data set which shows seasonality. Out of all other time series methods, winters method seems to separate the data and the noise better than the other methods hence we use winters method for processing of our data.

2.4.1.3 Unfiltered trend data

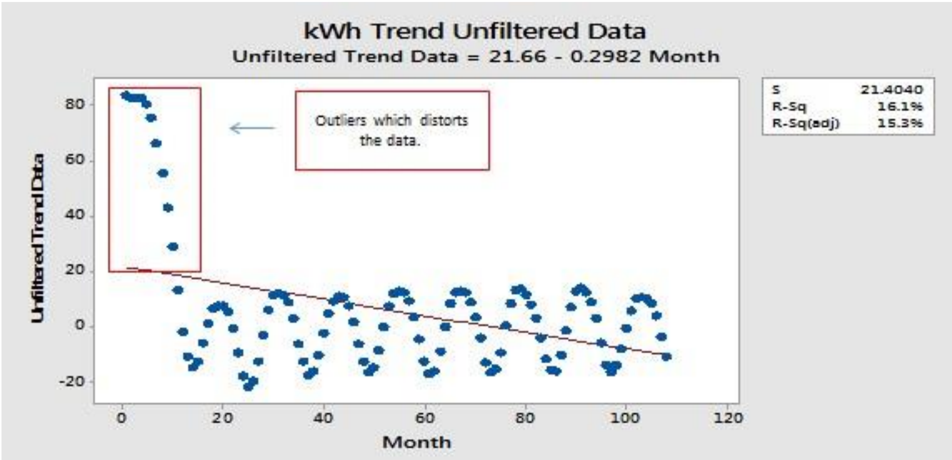


Figure 22: Outliers in the trend data

Winters method analyses the level component, trend component and the seasonal component on the data we have. Analysis of the trend component of the data shows an over estimation of trend which is not seen in our original data series. This also shows us that our initial assumption that degradation is linear is not true. These outliers have to be filtered either manually or needs to be automated using a program such as SAS or python. For this thesis, the data points have been removed manually.

2.4.1.4 Filtered trend data

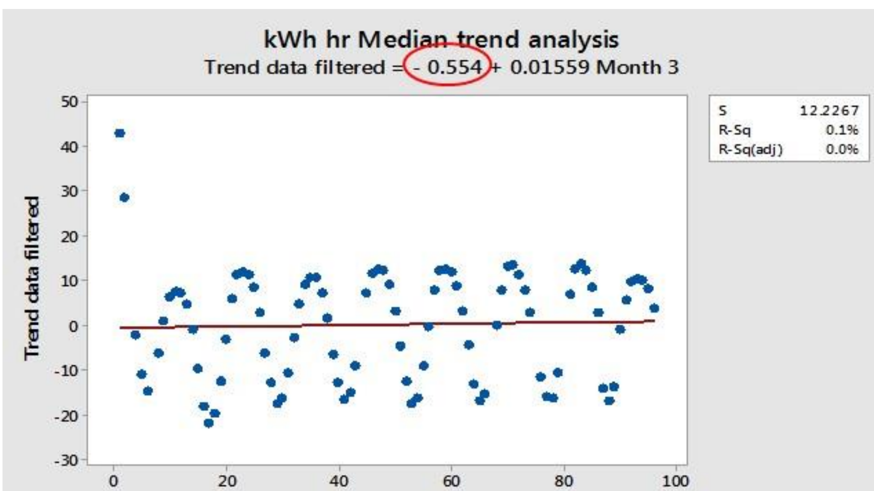


Figure 23: Regression graph with outliers removed

Removing the outliers present in the trend data gives us a straight line representing linear degradation. If the degradation of the power plant is linear, then the trend line we observe here must have a slope = 0. In order to find if the slope of the trend line is equal or not equal to 0, we perform hypothesis testing on the trend line. If the slope of the trend line is

0, then the Y intercept seen in the linear equation becomes the new slope which will be used in the formula for the calculation of degradation.

2.4.1.5 Hypothesis testing:

Test of $\mu = 0$ vs $\neq 0$

Variable	N	Mean	StDev	SE Mean	95% CI	T	**P**
Trend removed for outlier	121	-1.79	42.46	3.86	(-9.43, 5.85)	-0.46	**0.874**

When we perform hypothesis test, we hypothesize the slope of the regression line to be 0. The P-value which is the probability of our hypothesis being true. Here we see that the p value = 0.874. This means that there is an 87.4% probability that our hypothesis is correct, or in other words, the slope of the regression line obtained after removing the outliers is 0. Since the slope of the line is 0, the Y-intercept obtained in the regression equation becomes the new slope which will be used in the formula to calculate the degradation.

2.4.1.6 Calculation of degradation rate per year:

$$\% \text{ degradation / year} = \frac{(\beta 0 \text{ or } \beta 1) * 100 * 12}{\text{Median of Levels}} \quad \%/\text{year}$$

$$\text{Degradation rate } (\%/\text{year}) = \frac{(\beta_0 / \text{ median of levels}) * 100 * 12}{(1.386/1573.4) * 100 * 12}$$

= -1.34 %/ year (I-V degradation observed by ASU-PRL for Tempe Warehouse = 1.41%/year).

2.4.2 Model G

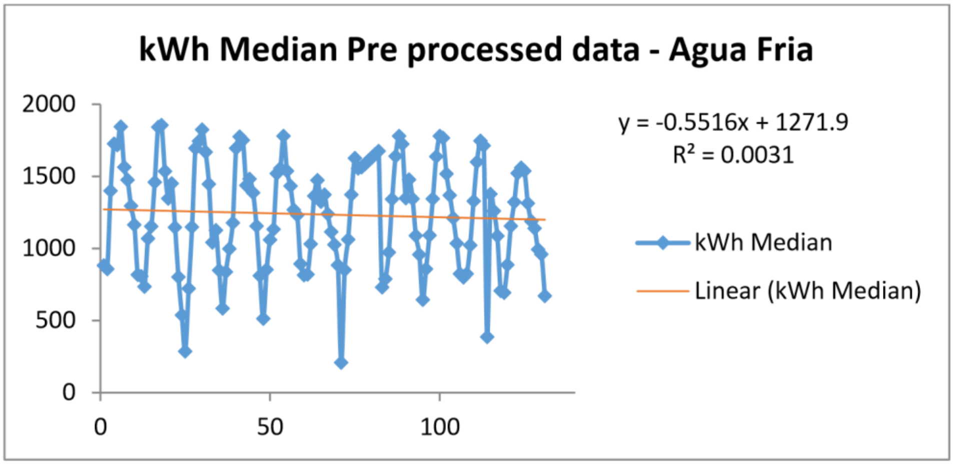


Figure 24: Preprocessed data for MODEL G

The Energy output is being recorded every 15 minutes by the Solar PV inverter. This energy produced is converted into hourly summation. The hourly summed energy is then averaged which gives us 12 data points for each year or 1 data point per each month. Graphing this data gives us the graph we see above and this is the preprocessed data which we use as input for statistical modelling based on time series methods.

2.4.2.1 Winters method on the preprocessed data:

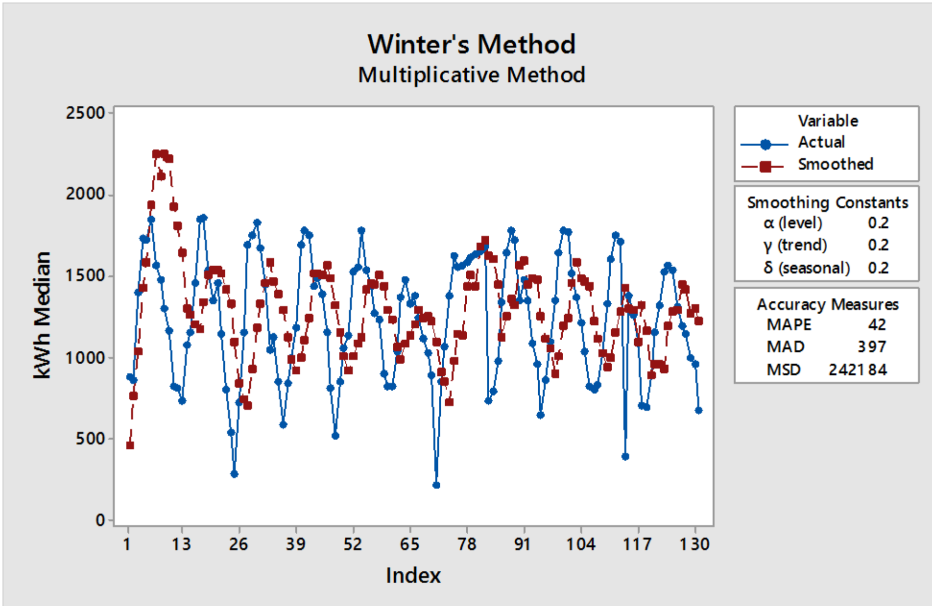


Figure 25: Winters method performed on MODEL G

The graph we see above shows us the difference between the actual and the smoothed data. This clearly tells us that modelling the actual data will not give us accurate results. Hence we use the smoothed data for performing our degradation calculations.

2.4.2.2 Residual analysis on the noise component

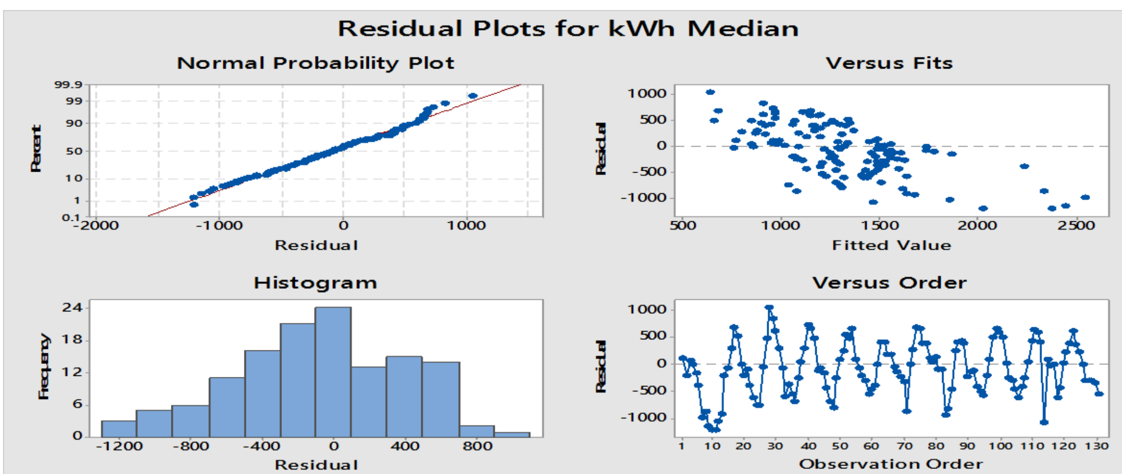


Figure 26: Residual (noise) analysis for MODEL G

The residual plot analysis the noise and tells us how well the data was separated from the noise. Our residual plots seem to satisfy the conditions of normality. The noise is normally distributed and has constant variance. The data also seems to be auto correlated based on the residual vs observation order plot which is expected for a data set which shows seasonality. Out of all other time series methods, winters method seems to separate the data and the noise better than the other methods hence we use winters method for processing of our data.

2.4.2.3 Unfiltered trend data

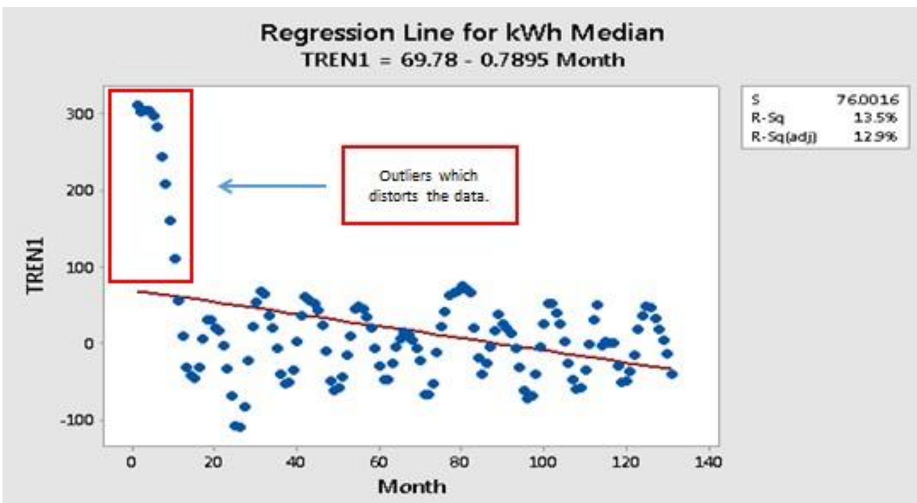


Figure 27: Unfiltered trend data

Winters method analyses the level component, trend component and the seasonal component on the data we have. Analysis of the trend component of the data shows an over estimation of trend which is not seen in our original data series. These trend values are used calculated by using the linear equation for trend along with estimations of slope and Yintercept. This also shows us that our initial assumption that degradation is linear is not true. These outliers have to be filtered either manually or needs to be automated using a program. For this thesis, the data points have been removed manually.

2.4.2.4 Filtered trend data

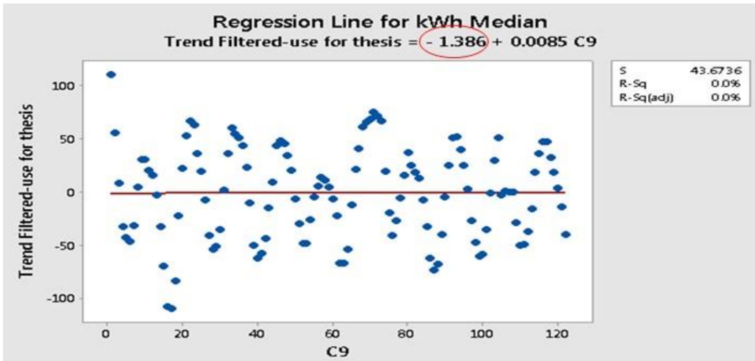


Figure 28: Filtered trend data

Removing the outliers present in the trend data gives us a straight line representing linear degradation. If the degradation of the power plant is linear, then the trend line we observe here must have a slope = 0. In order to find if the slope of the trend line is equal or not equal to 0, we perform hypothesis testing on the trend line. If the slope of the trend line is 0, then the Y intercept seen in the linear equation becomes the new slope which will be used in the formula for the calculation of degradation.

2.4.2.5 Hypothesis Test of μ = 0 vs ≠ 0

Variable	N	Mean	StDev	SE Mean	95% CI	T	P
Trend removed for outlier	121	-1.79	42.46	3.86	(-9.43, 5.85)	-0.46	0.644

When we perform hypothesis test, we hypothesize the slope of the regression line to be 0. The P-value which is the probability of our hypothesis being true. Here we see that the p value = 0.644. This means that there is a 64.4% probability that our hypothesis is correct, or in other words, the slope of the regression line obtained after removing the outliers is 0. Since the slope of the line is 0, the Y-intercept obtained in the regression equation becomes the new slope which will be used in the formula to calculate the degradation.

2.4.2.6 Calculation of degradation rate per year:

$$\% \text{ degradation / year} = \frac{(\beta 0 \text{ or } \beta 1) * 100 * 12}{\text{Median of Levels}} \quad \%/\text{year}$$

$$= (1.386/1573.4)*100*12$$

= 1.05 %/ year (I-V degradation observed by ASU-PRL for Agua Fria = 0.96%/year)

2.4.3 Linearity for Degradation in Hot – Dry Climatic condition (with HIT modules):

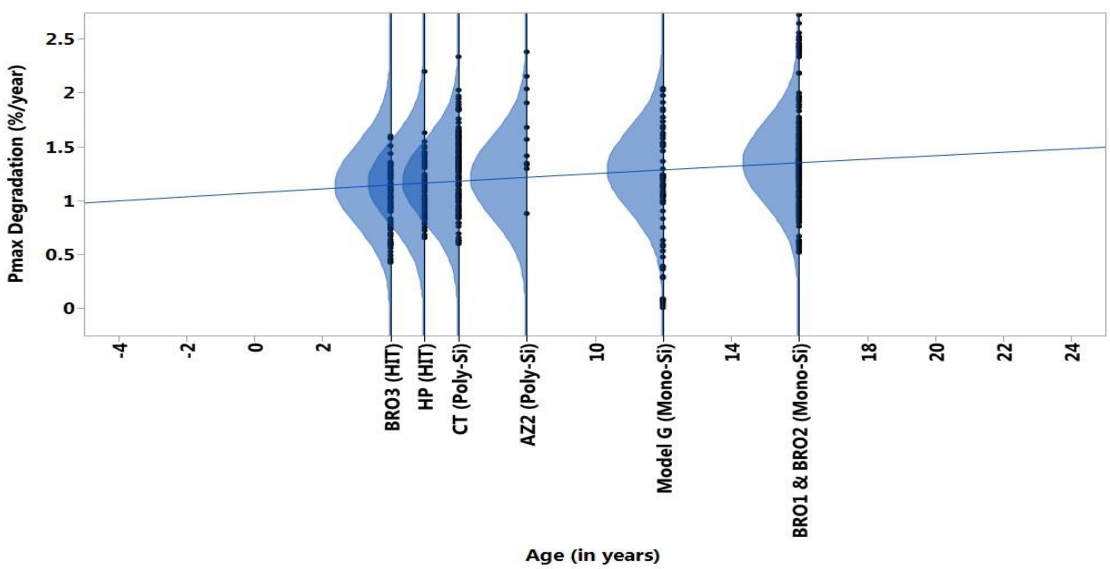


Figure 29: Degradation of power plants in hot dry climate with HIT modules

Assuming all c-Si modules degrade the same rate, a slight increase in degradation rate appears to happen in the aged modules as compared to the newer modules if HIT modules are included in the plot/analysis; however, it needs to be demonstrated with statistically significant number of plants for each climate and for each model.

2.4.4 Linearity for Degradation in Hot – Dry Climatic condition (without HIT modules):

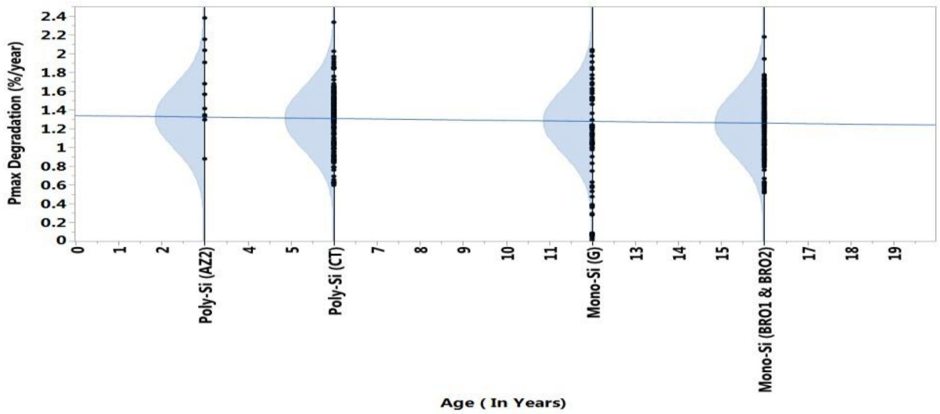


Figure 30: Degradation of power plants in the hot and dry climate without HIT modules

We can conclude based on the graph seen above that a negligibly small decrease in degradation rate appears to occur in the aged modules as compared to the newer modules if HIT modules are not included in the plot/analysis; however, it needs to be demonstrated with statistically significant number of plants for each climate and for each model.

2.5 CONCLUSION

In the second part, a statistical degradation analysis is performed to determine if the degradation rates are linear or not in the power plants exposed in a hot-dry climate for the crystalline silicon technologies. This linearity degradation analysis is performed using the data obtained through two methods: current-voltage method; metered kWh method. For the current-voltage method, the annual power degradation data of hundreds of individual modules in six crystalline silicon power plants of different ages is used. This method involves going to the plant in person along with several equipment (such as I-V curve tracer, thermocouples, reference cells, etc.). In this method, the best, median and worst strings are statistically selected, and the I-V curves are performed on the modules from the statistically selected best, median and worst strings. This process takes several days to come up with a value for degradation rate for each plant depending on the size of the plant. This preliminary study, based on four plants data obtained in a hot-dry climate, appears to indicate that the crystalline silicon modules in hot-dry climate degrade linearly with respect to time.

For the metered kWh method, the hourly kWh data secured from two powers plant was used. This method, in principle, should consume less amount of time to determine the degradation rate as it does not involve test personnel going to the PV plant sites. However, the metered kWh data typically consists of the signal and noise components. So, removing noise component on the degradation rate determination becomes critical. Smoothers remove the noise component from the data by taking the average of the current and the previous observations. Once this is done, a residual plot analysis of the error component is performed to determine the noise was successfully separated from the data by proving the noise is random. A residual plot analysis using Winters' statistical method is performed for two crystalline silicon plants of different ages in a hot-dry climate. This analysis also appears to indicate that the degradation in hot-dry climate for the crystalline silicon modules is linear. It is important to note that this linearity analysis and conclusion have been done based on only a limited number of power plants. Therefore, it is recommended to extend this study to more number of power plants in diverse climatic conditions for different technologies. This entire procedure could be automated using some software such as SAS or Python.

REFERENCES:

1) M. A. Quintana, D. L. King, T. J. McMohan, and C. R. Osterwald, “Commonly observed degradation in field-aged photovoltaic modules,” 29th IEEE Photovoltaic Specialists Conference, New Orleans, LA, USA, 2002, pp. 1436–1439

2) D. C. Jordan and S. R. Kurtz, “Photovoltaic Degradation Rates — An Analytical Review, NREL/JA-5200-51664, June 2012

3) S. Shrestha, J. Mallineni, K. Yedidi, B. Knisely, S. Tatapudi, J. Kuitche, and G. TamizhMani, “Determination of Dominant Failure Modes Using FMECA on the Field Deployed c-Si Modules Under Hot-Dry Desert Climate”, IEEE Journal of Photovoltaics, vol.5, no.1, pp.174-182, Jan. 2015.

4) Mathan Kumar Moorthy, “Automation of Risk Priority Number Calculation of Photovoltaic Modules and Evaluation of Module Level Power Electronics” MS Thesis, Arizona State University, December 2015.

5) J. Kuitche and G. TamizhMani, “Accelerated Lifetime Testing of Photovoltaic Modules”.

6) M. A. Quintana, D. L. King, T. J. McMohan, and C. R. Osterwald, “Commonly observed degradation in field-aged photovoltaic modules,” 29th IEEE Photovoltaic Specialists Conference, New Orleans, LA, USA, pp. 1436–1439, 2002.

7) Source- en.wikipedia.org/wiki/Balance_of_system.

8) Analysis Techniques for System Reliability: Procedure for Failure Mode and Effects Analysis (FMEA), IEC Std. 60812, 2006

9) Y. Xue, K. C. Divya, G. Griepentrog, M. Liviu, S. Suresh, and M. Manjrekar, "Towards Next Generation Photovoltaic Inverters," IEEE Energy Conversion Congress and Exposition (ECCE), 2011.

(10) W. Bower and D. Ton, "Summary Report on the DOE High-tech Inverter Workshop," DOE Office of Energy Efficiency and Renewable Energy, 2005.

(11) http://rredc.nrel.gov/solar/calculators/pvwatts/system.html

(12) N. Umachandran, J. Kuitche, G. TamizhMani, "Statistical Methods to Determine Dominant Degradation Modes of Fielded PV Modules", IEEE PVSC, 2015.

13) Sanjay Shrestha,"Determination of Dominant Failure Modes using Combined Experimental and Statistical Method to Calculate Degradation Rates",MS Thesis, Arizona State University, 2013,(repository.asu.edu).

(14) V. Rajasekar, "Indoor Soiling Method and Outdoor Statistical Risk Analysis of Photovoltaic Power Plants", MS Thesis, Arizona State University, 2014 (repository.asu.edu).

(15) S.Boppana, "Outdoor Soiling Loss Characterization and Statistical Risk Analysis of Photovoltaic Power Plants", MS Thesis, Arizona State University, 2014 (repository.asu.edu).

(16) C. E. Packard, J. H. Wohlegemuth, and S. R. Kurtz, "Development of a visual inspection data collection tool for evaluation of fielded PV module condition," Nat. Renew. Energy Lab., Golden, CO, USA, Tech. Rep. NREL/TP-5200-56154, Aug. 2012.

(17) https://en.wikipedia.org/wiki/Errors_and_residuals.

(18) http://www.dfrsolutions.com/uploads/courses/SPI2012.pdf

(20) W. Bower and D. Ton, "Summary Report on the DOE High-tech Inverter Workshop," DOE Office of Energy Efficiency and Renewable Energy, 2005.

(21) http://rredc.nrel.gov/solar/calculators/pvwatts/system.html

(25) https://www.otexts.org/fpp/7/5

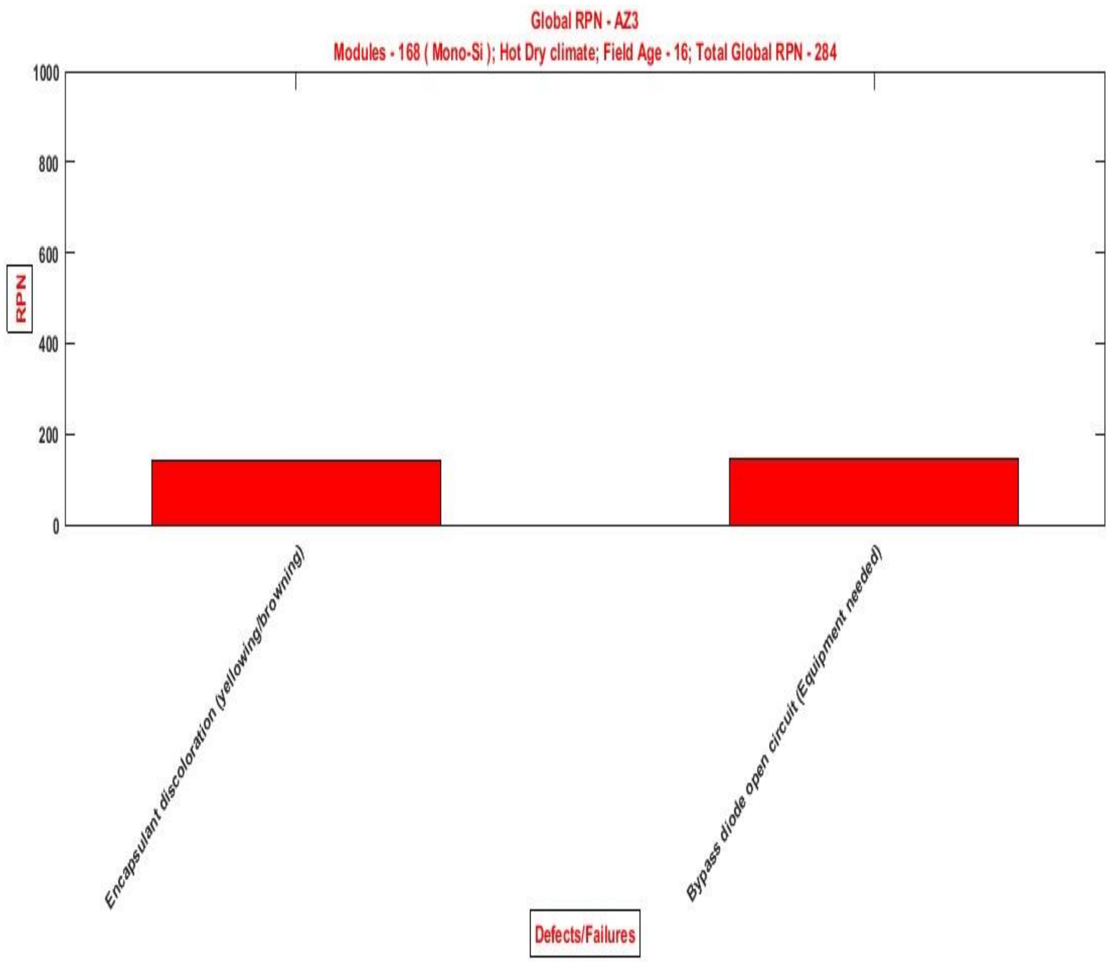
(26) Douglas C. Montgomery, Cheryl L.Jennings and Murat Kulahci, “Introduction to time series analysis and forecasting”, Wiley Series in Probability and Statistics,2008.

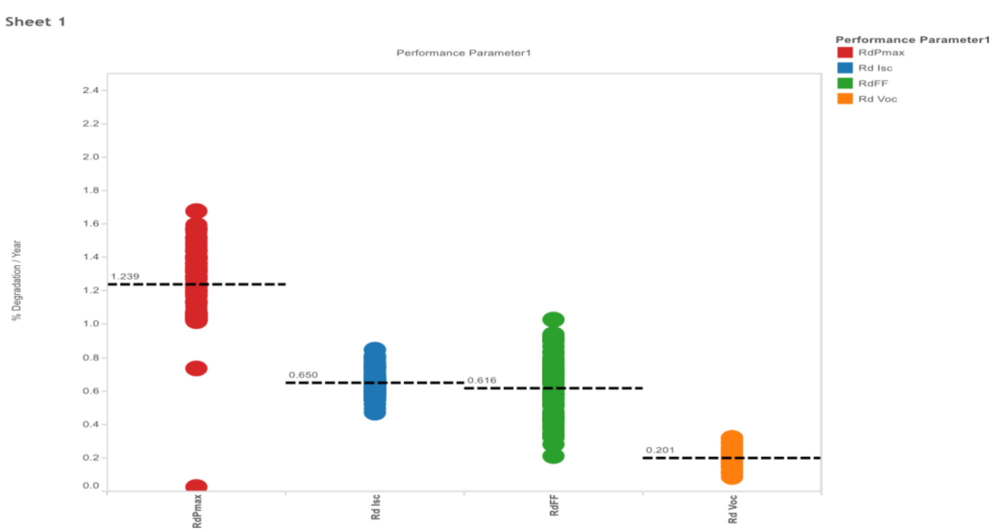
(27) J. Mallineni, B. Knisely, K. Yedidi, S. Tatapudi, J. Kuitche and G. TamizhMani, "Evaluation of 12-Year Old PV Power Plant in Hot – Dry Desert Climate: Potential Use of Field Failure Metrics for Financial Risk Calculation", 40th IEEE Photovoltaic Specialists Conference, pp. 3366 – 3371, 2014.

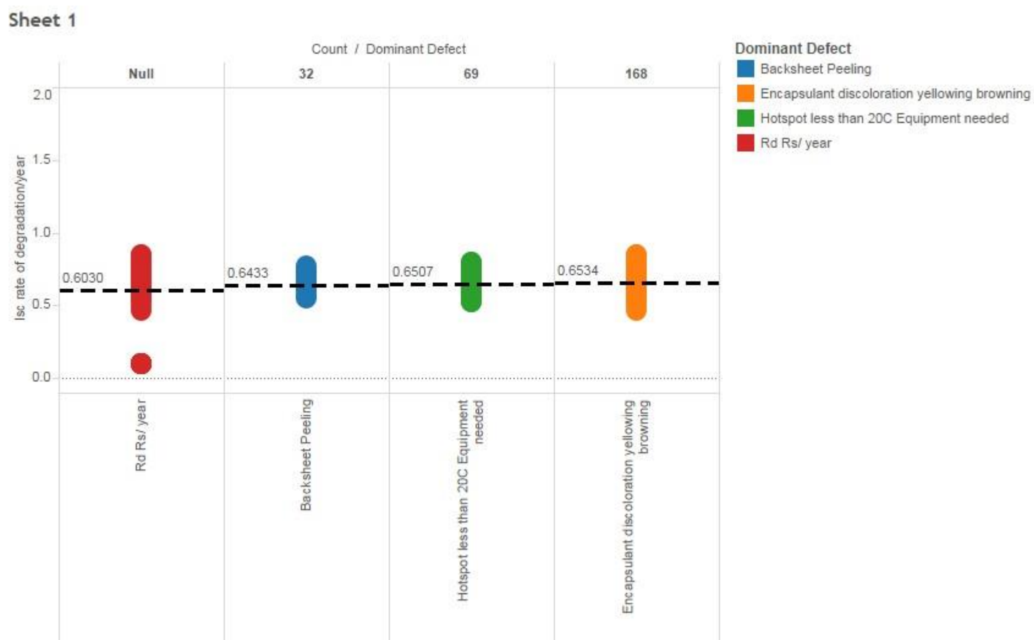
(28) Marc Köntges, Sarah Kurtz, Corinne Packard, Ulrike Jahn, Karl A. Berger, “Review of Failures of photovoltaic modules”, Report IEA-PVPS T13-01:2014, Photovoltaic Power system program.

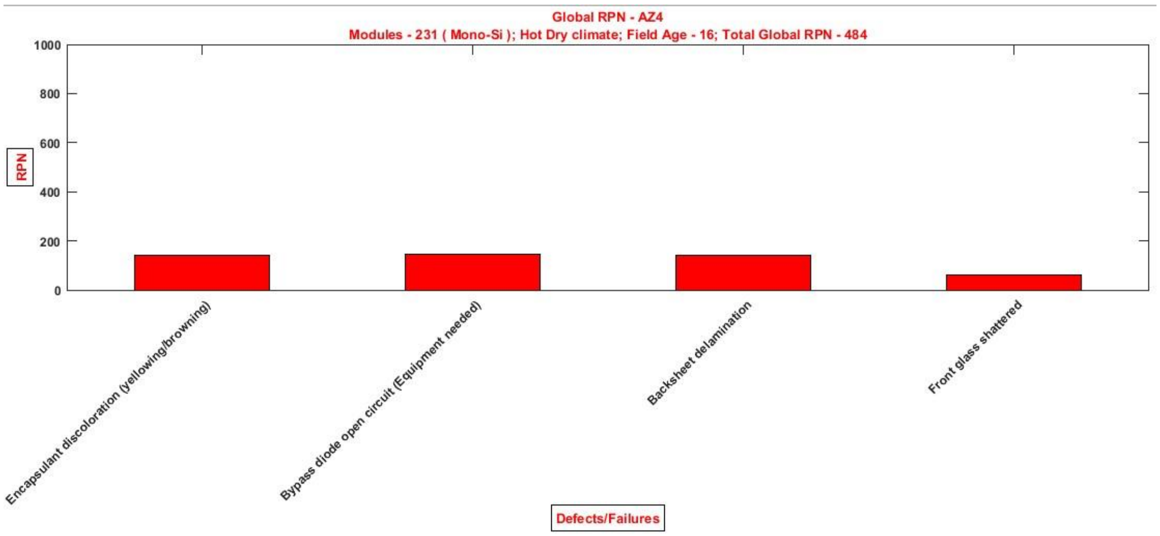
APPENDIX A

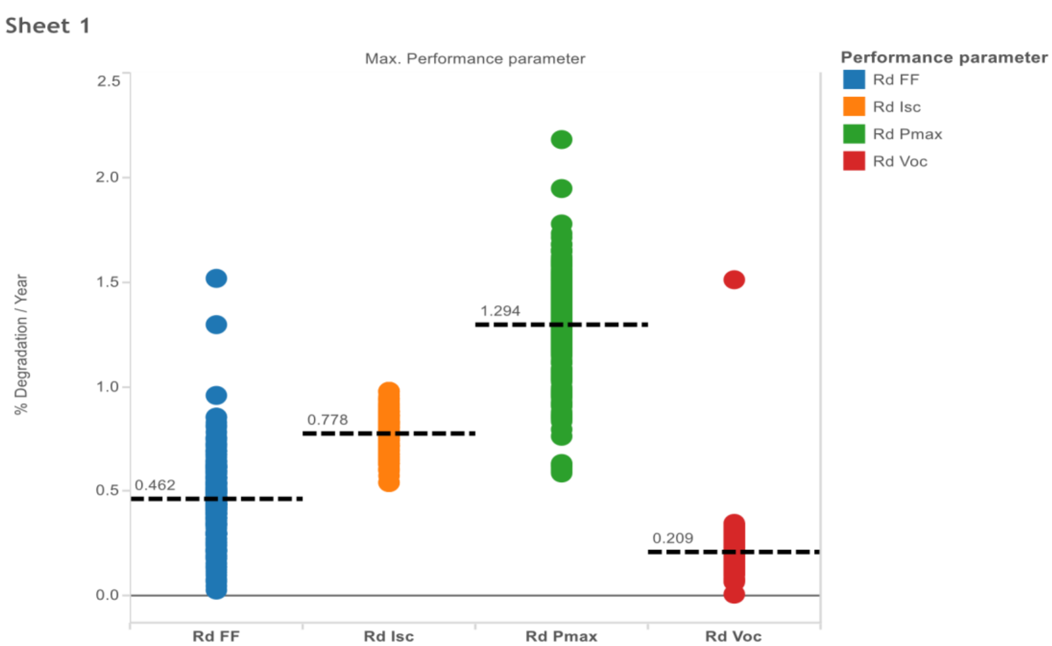
DATA COLLECTED MAY 1998 - MAY 2014


Global RPN - AZ3
Modules - 168 (Mono-Si); Hot Dry climate; Field Age - 16; Total Global RPN - 284
RPN
1000
800
600
400
200
0
Encapsulant discoloration (yellowing/browning)
Bypass diode open circuit (Equipment needed)
Defects/Failures

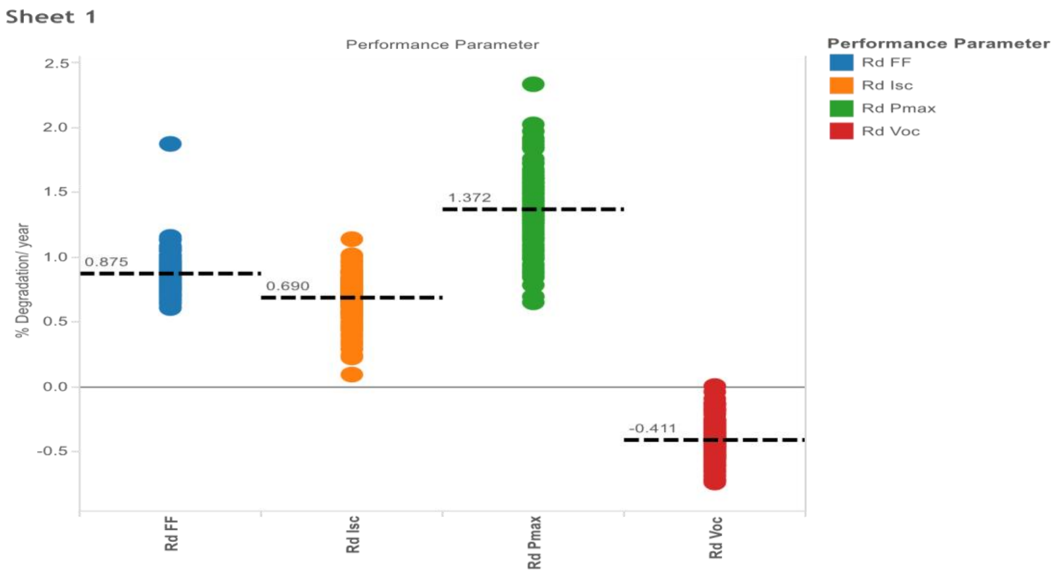

Sheet 1
Performance Parameter1
Performance Parameter1
RdPmax
Rd Isc
RdFF
Rd Voc
% Degradation / Year
2.4
2.2
2.0
1.8
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
1.239
0.650
0.616
0.201
RdPmax
Rd Isc
RdFF
Rd Voc

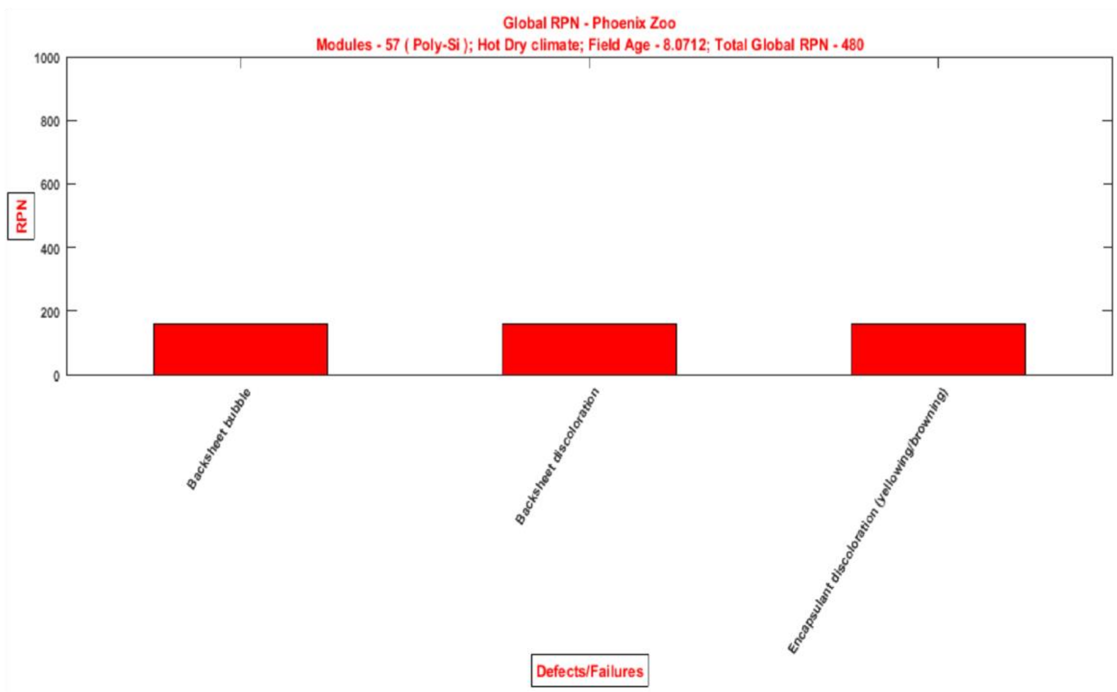

Sheet 1
Count / Dominant Defect
Null
32
69
168
Isc rate of degradation/year
2.0
1.5
1.0
0.5
0.0
0.6030
0.6433
0.6507
0.6534
Rd Rs/ year
Backsheet Peeling
Hotspot less than 20C Equipment needed
Encapsulant discoloration yellowing browning
Dominant Defect
Backsheet Peeling
Encapsulant discoloration yellowing browning
Hotspot less than 20C Equipment needed
Rd Rs/ year

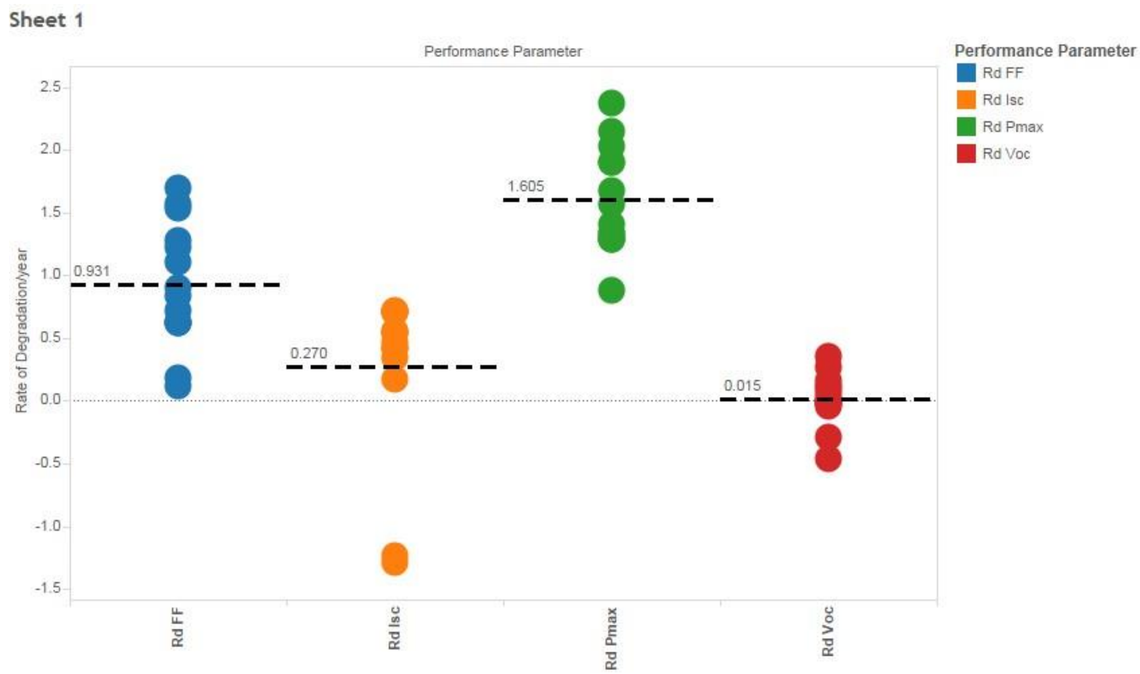

Global RPN - AZ4
Modules - 231 (Mono-Si); Hot Dry climate; Field Age - 16; Total Global RPN - 484
RPN
1000
800
600
400
200
0
Encapsulant discoloration (yellowing/browning)
Bypass diode open circuit (Equipment needed)
Backsheet delamination
Front glass shattered
Defects/Failures

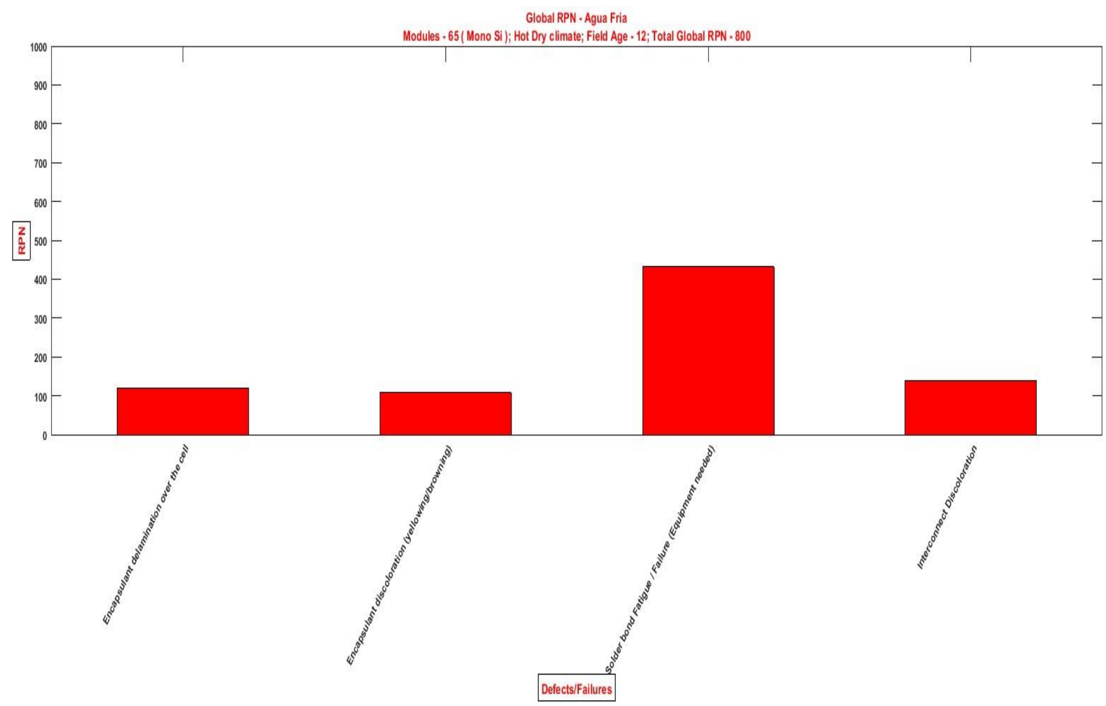

Sheet 1
Max. Performance parameter
Performance parameter
Rd FF
Rd Isc
Rd Pmax
Rd Voc
% Degradation / Year
2.5
2.0
1.5
1.0
0.5
0.0
0.462
0.778
1.294
0.209
Rd FF
Rd Isc
Rd Pmax
Rd Voc

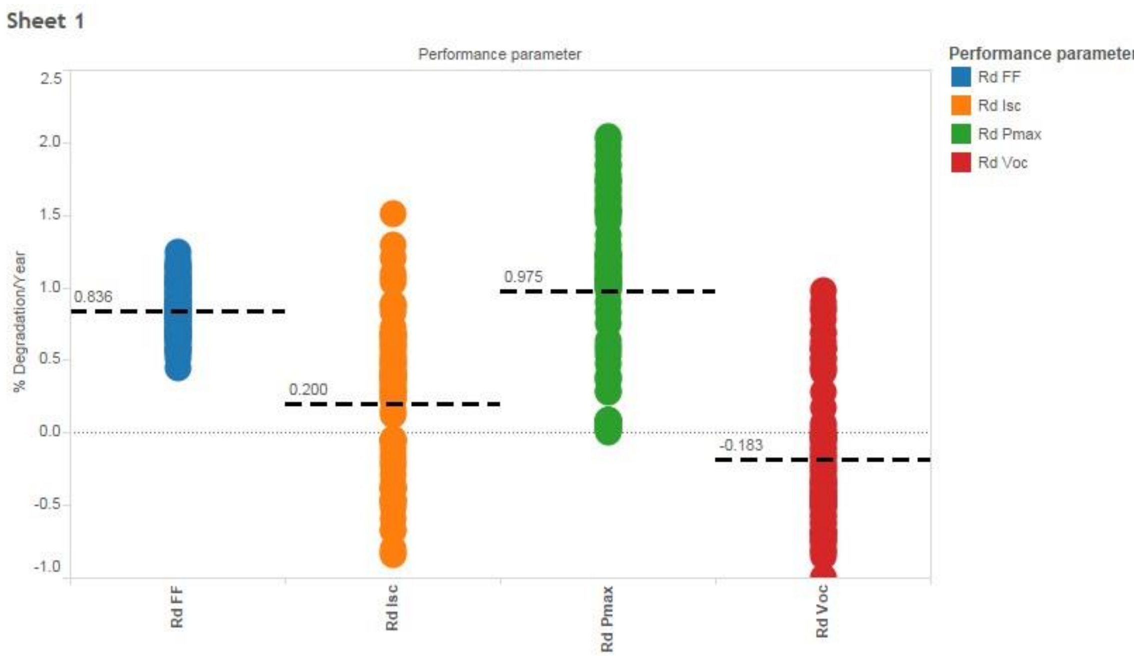

Sheet 2
Count / Dominant Defect
231
% Degradation/ Year
2.5
2.0
1.5
1.0
0.5
0.0
0.7781
0.7781
0.7444
Encapsulant discoloration yellowing browning
Frontglasslightlysoiled
Rd Rs / year
Dominant Defect
Encapsulant discoloration yellowing browning
Frontglasslightlysoiled
Rd Rs / year


Sheet 1
Performance Parameter
Performance Parameter
Rd FF
Rd Isc
Rd Pmax
Rd Voc
% Degradation/ year
2.5
2.0
1.5
1.0
0.5
0.0
-0.5
0.875
0.690
1.372
-0.411
Rd FF
Rd Isc
Rd Pmax
Rd Voc

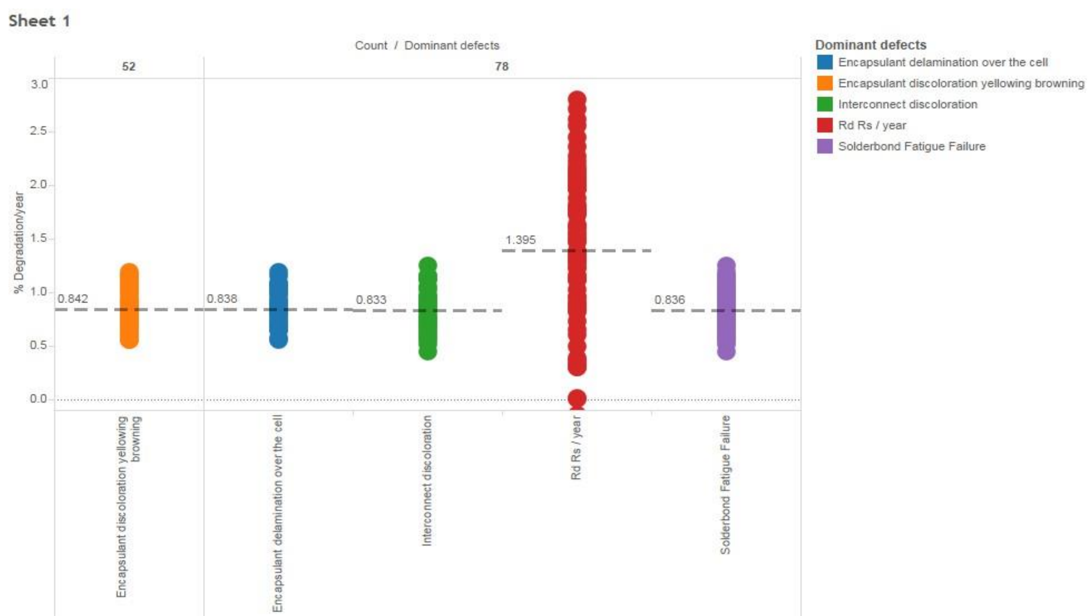

Global RPN - Phoenix Zoo
Modules - 57 (Poly-Si); Hot Dry climate; Field Age - 8.0712; Total Global RPN - 480
RPN
1000
800
600
400
200
0
Backsheet bubble
Backsheet discoloration
Encapsulant discoloration (yellowing/browning)
Defects/Failures


Sheet 1
Performance Parameter
Rate of Degradation/year
0.931
0.270
1.605
0.015
Rd FF
Rd Isc
Rd Pmax
Rd Voc
Performance Parameter
Rd FF
Rd Isc
Rd Pmax
Rd Voc


Global RPN - Agua Fria
Modules - 65 (Mono Si); Hot Dry climate; Field Age - 12; Total Global RPN - 800
RPN
Encapsulant delamination over the cell
Encapsulant discoloration (yellowing/browning)
Solder bond Fatigue / Failure (Equipment needed)
Interconnect Discoloration
Defects/Failures

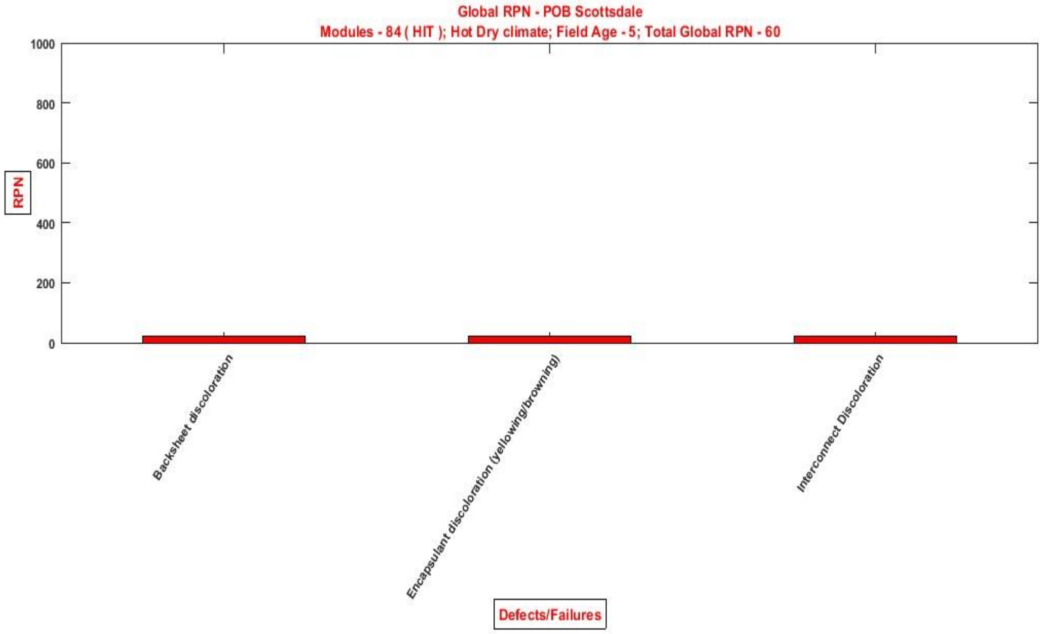


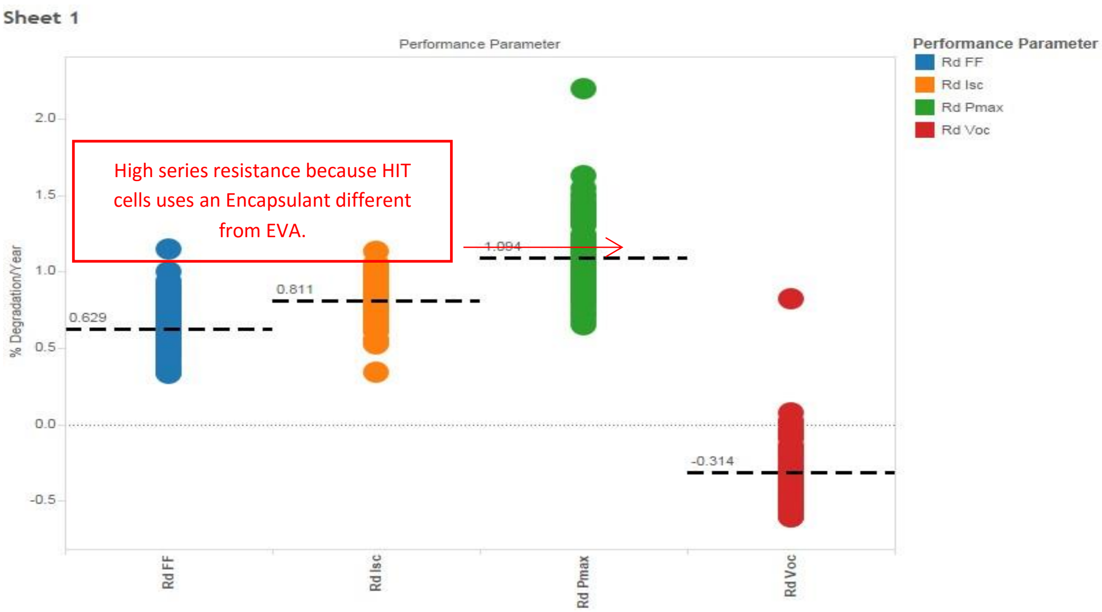
Sheet 1
Performance parameter
Performance parameter
Rd FF
Rd Isc
Rd Pmax
Rd Voc
% Degradation/Year
2.5
2.0
1.5
1.0
0.5
0.0
-0.5
-1.0
0.836
0.200
0.975
-0.183
Rd FF
Rd Isc
Rd Pmax
Rd Voc

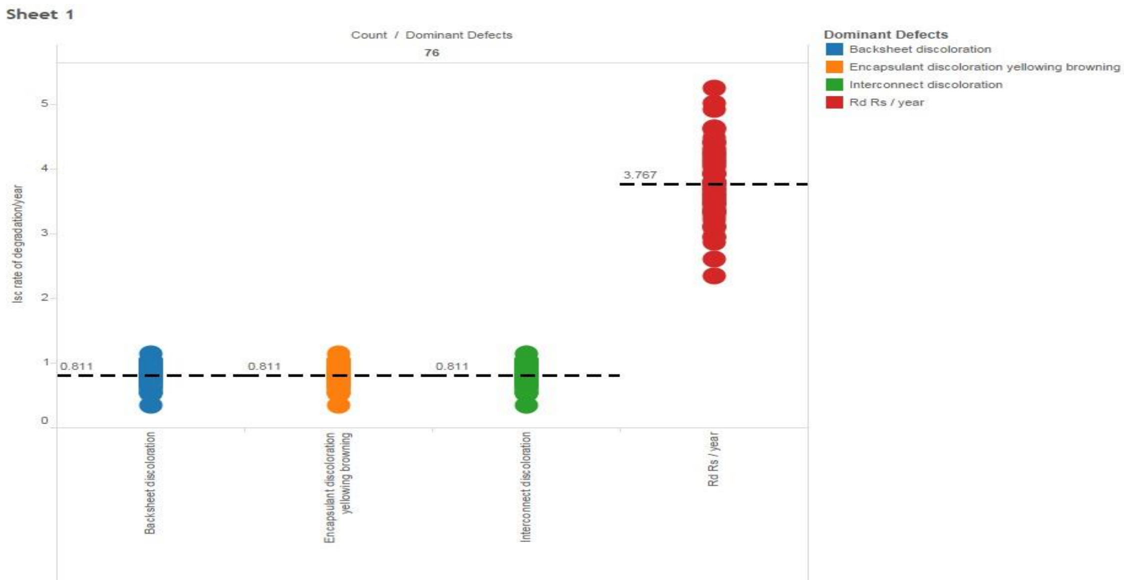


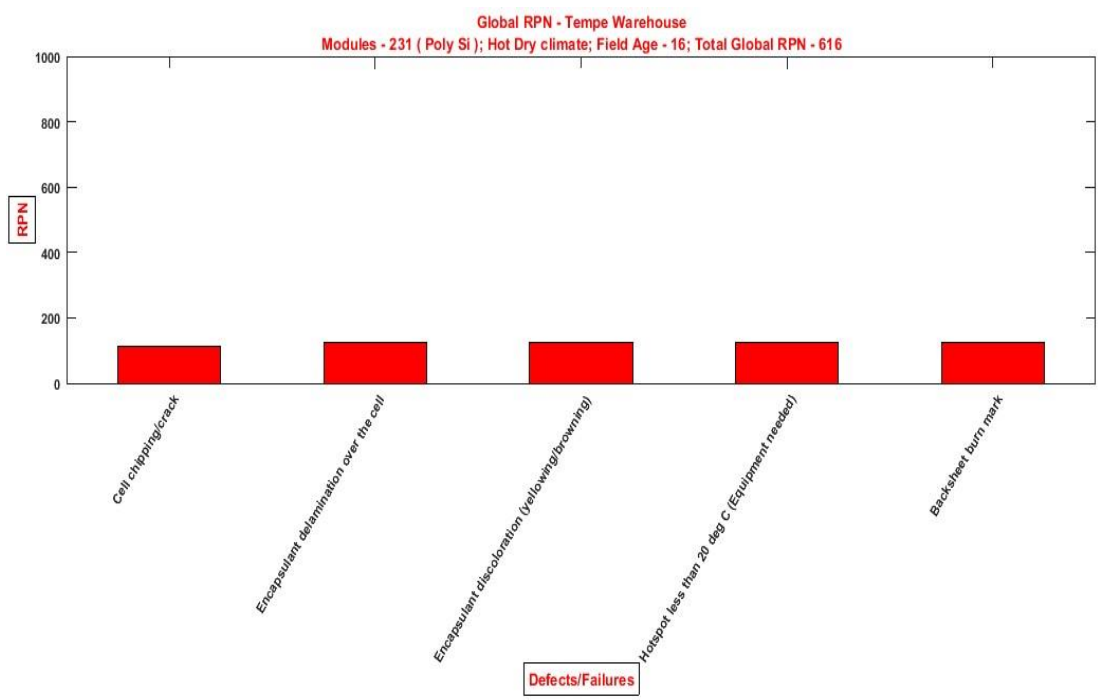
Sheet 1
Count / Dominant defects
52
78
Dominant defects
Encapsulant delamination over the cell
Encapsulant discoloration yellowing browning
Interconnect discoloration
Rd Rs / year
Solderbond Fatigue Failure
% Degradation/year
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0.842
0.838
0.833
1.395
0.836
Encapsulant discoloration yellowing browning
Encapsulant delamination over the cell
Interconnect discoloration
Rd Rs / year
Solderbond Fatigue Failure

AZ7 RPN

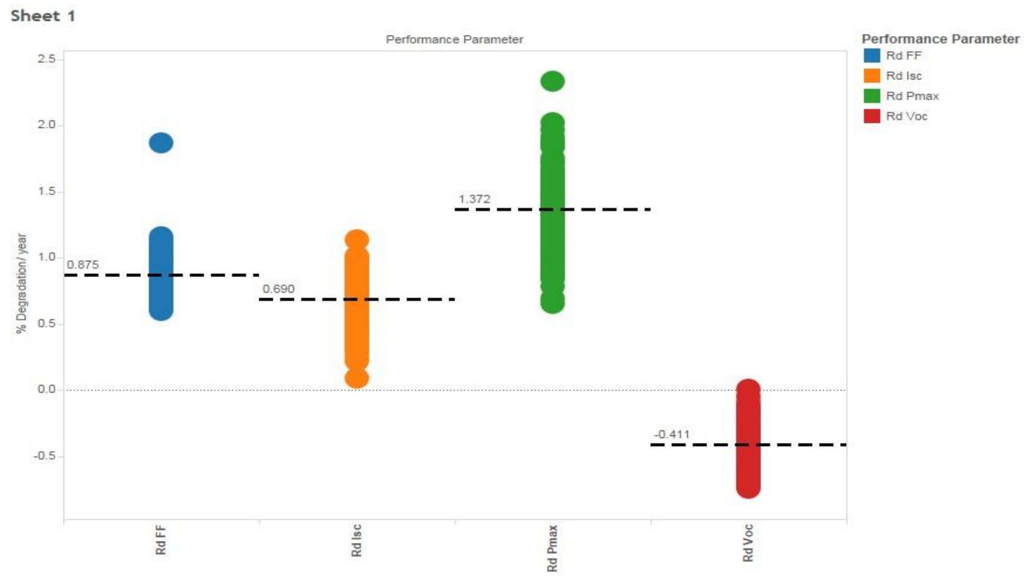

Global RPN - POB Scottsdale
Modules - 84 (HIT); Hot Dry climate; Field Age - 5; Total Global RPN - 60
RPN
1000
800
600
400
200
0
Backsheet discoloration
Encapsulant discoloration (yellowing/browning)
Interconnect Discoloration
Defects/Failures

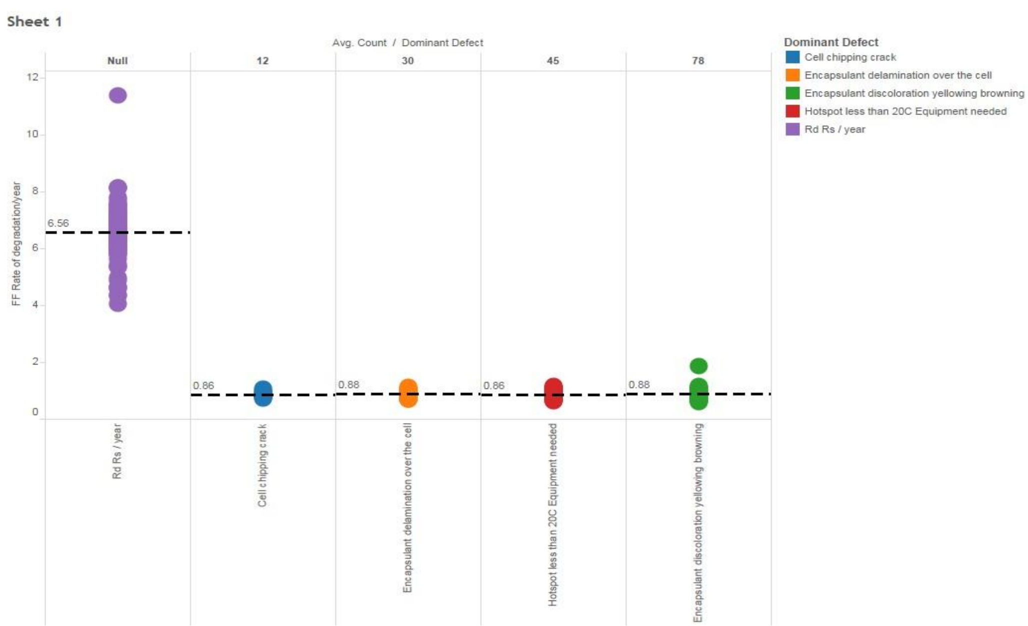

Sheet 1
Performance Parameter
Performance Parameter
Rd FF
Rd Isc
Rd Pmax
Rd Voc
% Degradation/Year
2.0
1.5
1.0
0.5
0.0
-0.5
High series resistance because HIT cells uses an Encapsulant different from EVA.
0.629
0.811
1.094
-0.314
Rd FF
Rd Isc
Rd Pmax
Rd Voc

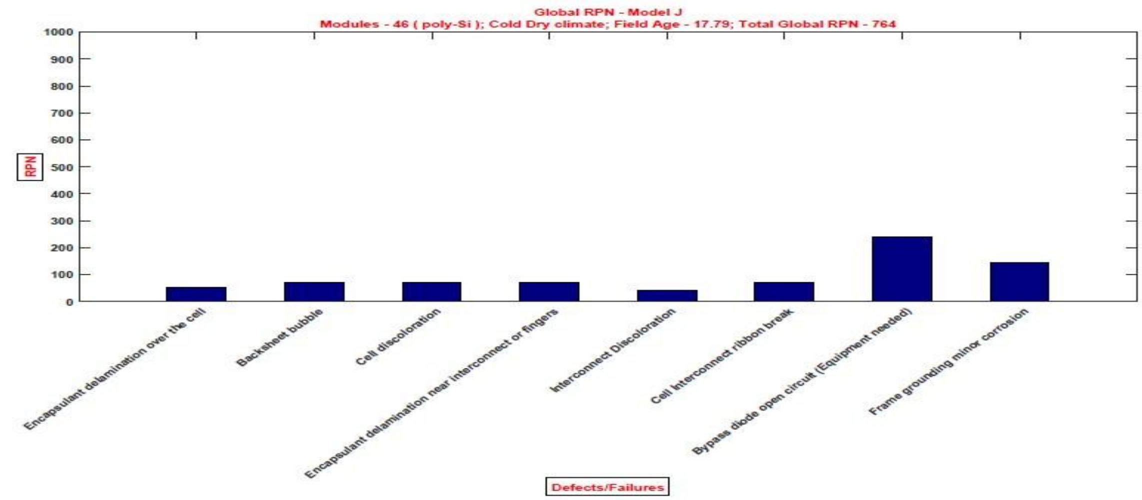


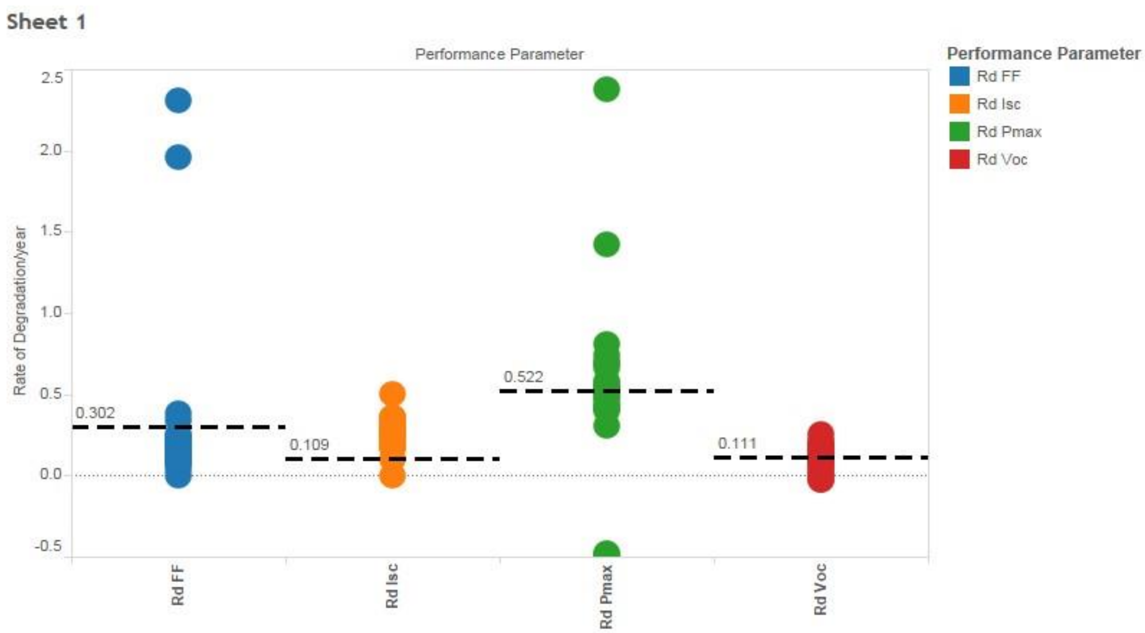


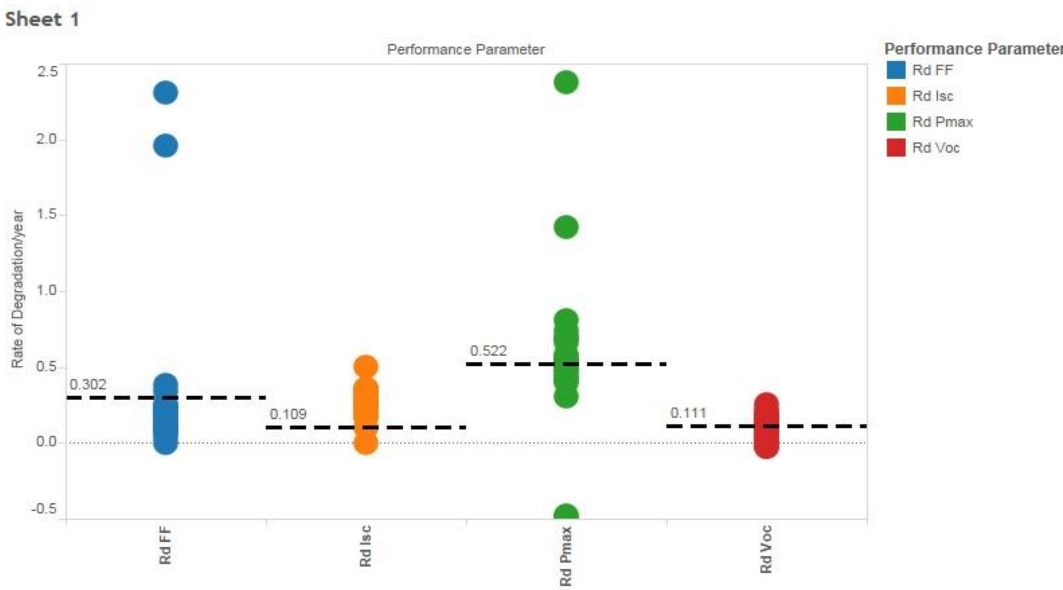
AZ8 Affected Performance Parameter

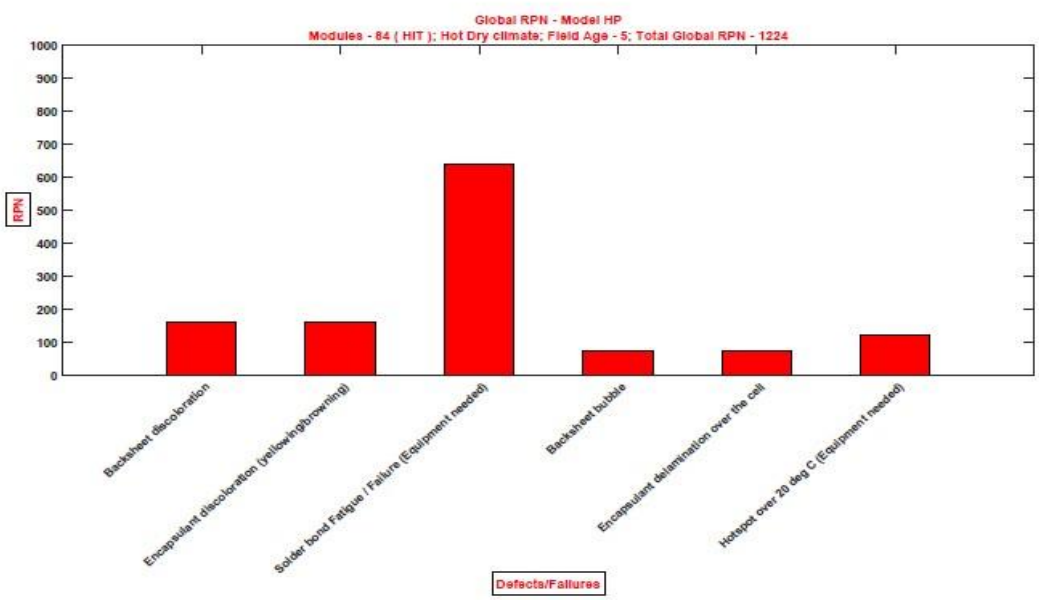

Sheet 1
Performance Parameter
Performance Parameter
Rd FF
Rd Isc
Rd Pmax
Rd Voc
% Degradation/ year
2.5
2.0
1.5
1.0
0.5
0.0
-0.5
0.875
0.690
1.372
-0.411
Rd FF
Rd Isc
Rd Pmax
Rd Voc

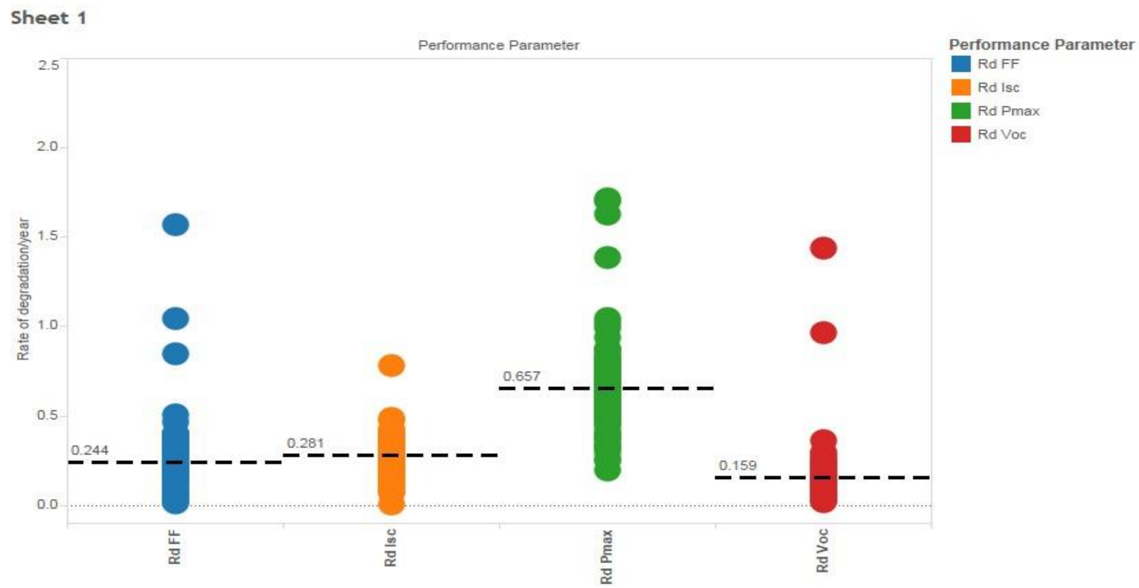

Sheet 1
Avg. Count / Dominant Defect
Null
12
30
45
78
Dominant Defect
Cell chipping crack
Encapsulant delamination over the cell
Encapsulant discoloration yellowing browning
Hotspot less than 20C Equipment needed
Rd Rs / year
FF Rate of degradation/year
12
10
8
6
4
2
0
6.56
0.86
0.88
0.86
0.88
Rd Rs / year
Cell chipping crack
Encapsulant delamination over the cell
Hotspot less than 20C Equipment needed
Encapsulant discoloration yellowing browning

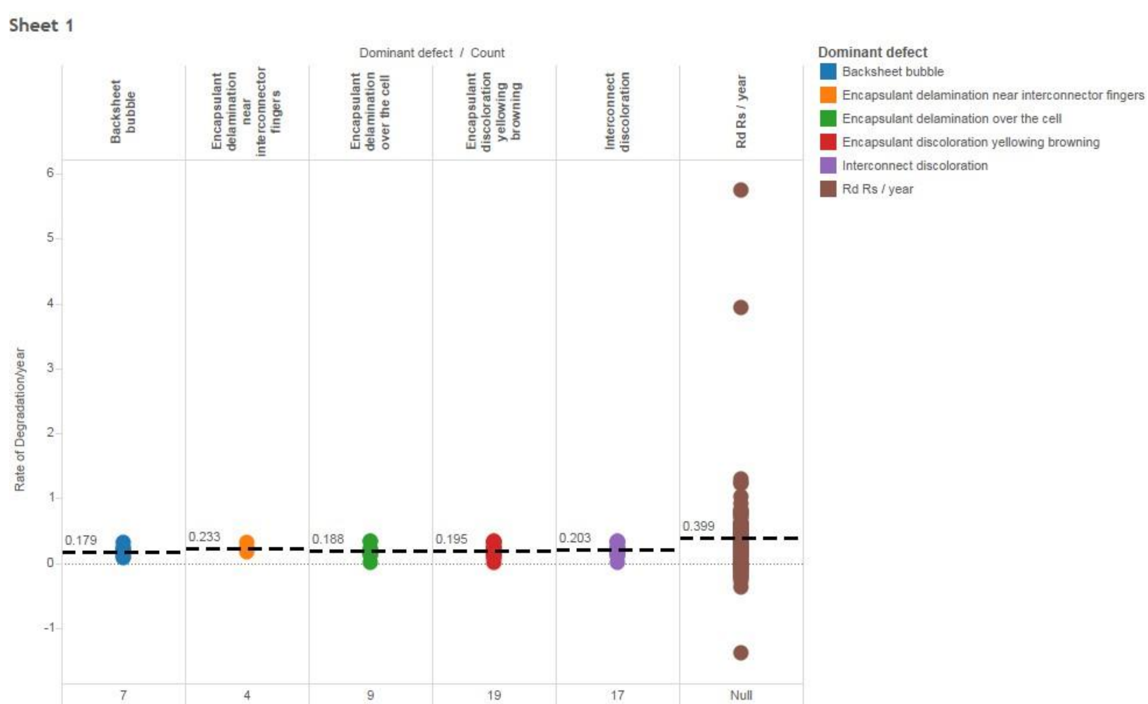

Global RPN - Model J
Modules - 46 (poly-Si); Cold Dry climate; Field Age - 17.79; Total Global RPN - 764
RPN
Defects/Failures
Encapsulant delamination over the cell
Backsheet bubble
Cell discoloration
Encapsulant delamination near interconnect or fingers
Interconnect Discoloration
Cell interconnect ribbon break
Bypass diode open circuit (Equipment needed)
Frame grounding minor corrosion

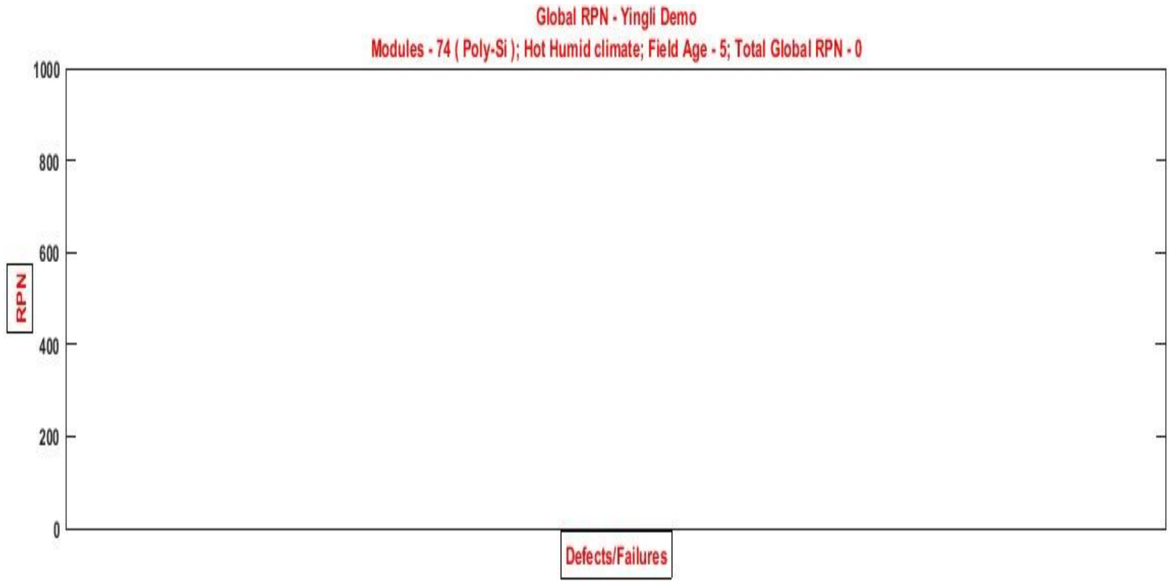

Sheet 1
Performance Parameter
Rate of Degradation/year
0.302
0.109
0.522
0.111
Rd FF
Rd Isc
Rd Pmax
Rd Voc

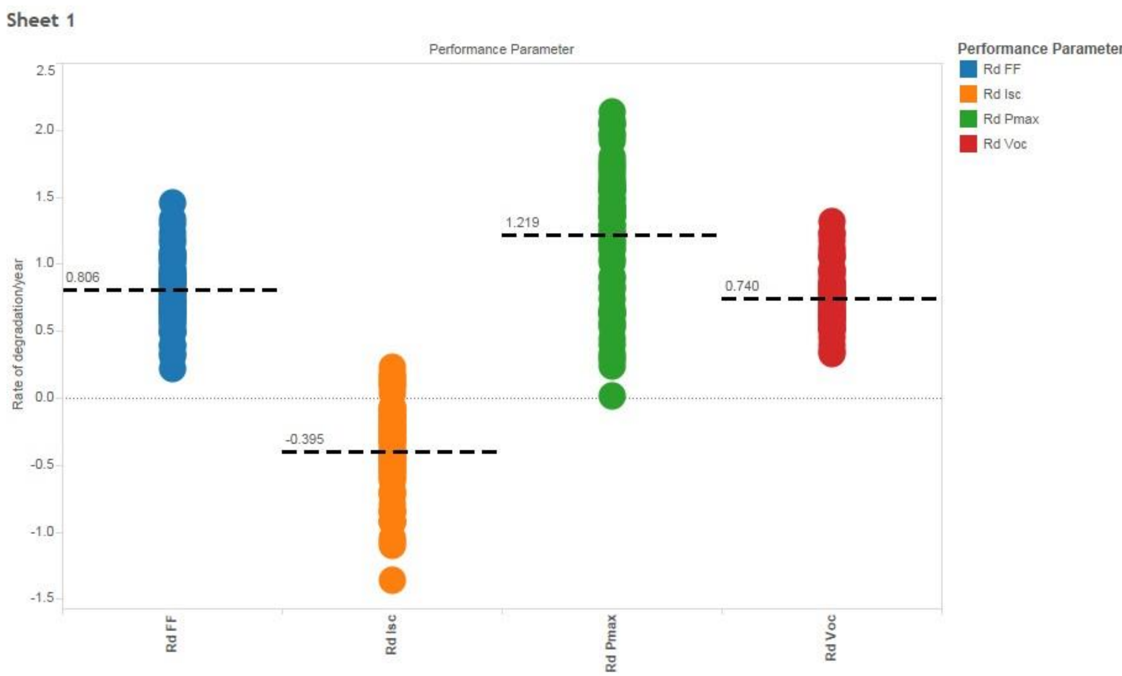

Sheet 1
Performance Parameter
Rate of Degradation/year
2.5
2.0
1.5
1.0
0.5
0.0
-0.5
0.302
0.109
0.522
0.111
Rd FF
Rd Isc
Rd Pmax
Rd Voc
Performance Parameter
Rd FF
Rd Isc
Rd Pmax
Rd Voc

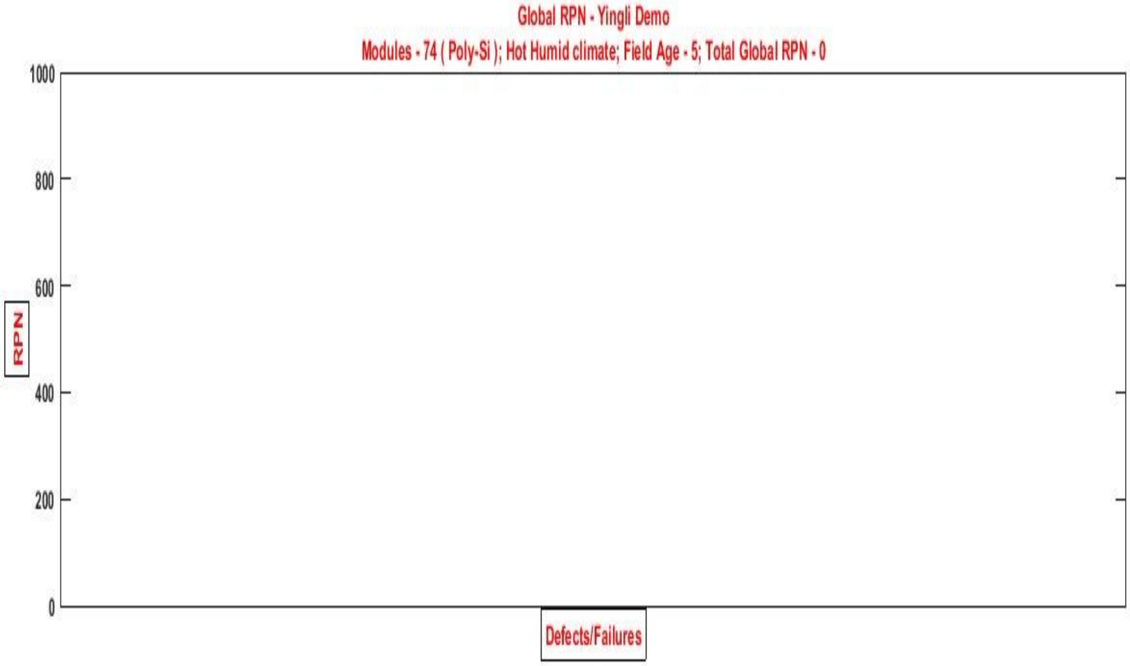

Global RPN - Model HP
Modules - 84 (HIT); Hot Dry climate; Field Age - 5; Total Global RPN - 1224
RPN
1000
900
800
700
600
500
400
300
200
100
0
Backsheet discoloration
Encapsulant discoloration (yellowing/browning)
Solder bond Fatigue / Failure (Equipment needed)
Backsheet bubble
Encapsulant delamination over the cell
Hotspot over 20 deg C (Equipment needed)
Defects/Failures


Sheet 1
Performance Parameter
Rate of degradation/year
0.244
0.281
0.657
0.159
Rd FF
Rd Isc
Rd Pmax
Rd Voc
Performance Parameter
Rd FF
Rd Isc
Rd Pmax
Rd Voc

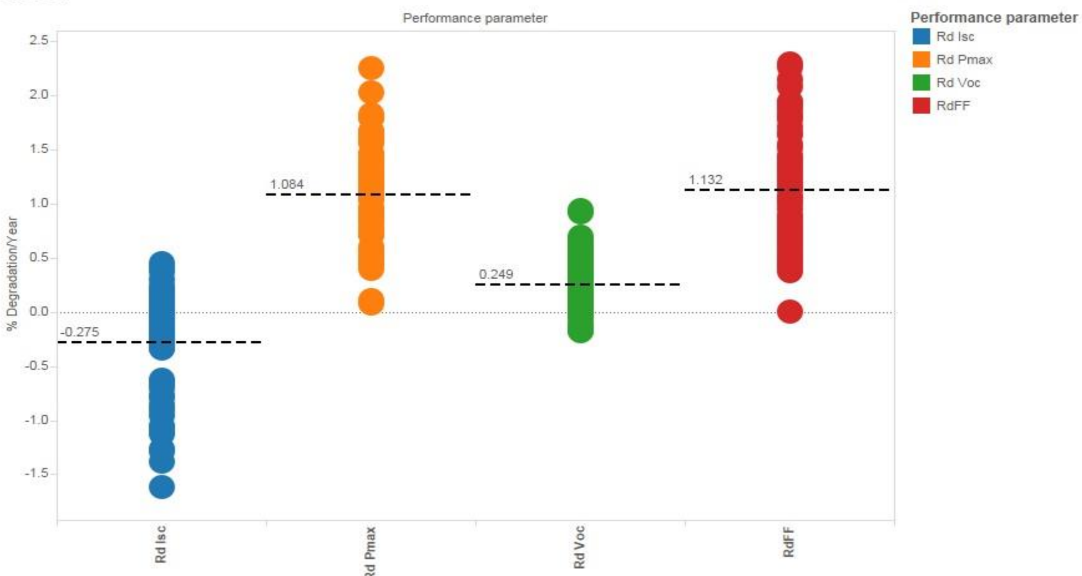

Sheet 1
Dominant defect / Count
Backsheet bubble
Encapsulant delamination near interconnector fingers
Encapsulant delamination over the cell
Encapsulant discoloration yellowing browning
Interconnect discoloration
Rd Rs / year
Rate of Degradation/year
0.179
0.233
0.188
0.195
0.203
0.399
7
4
9
19
17
Null
Dominant defect
Backsheet bubble
Encapsulant delamination near interconnector fingers
Encapsulant delamination over the cell
Encapsulant discoloration yellowing browning
Interconnect discoloration
Rd Rs / year

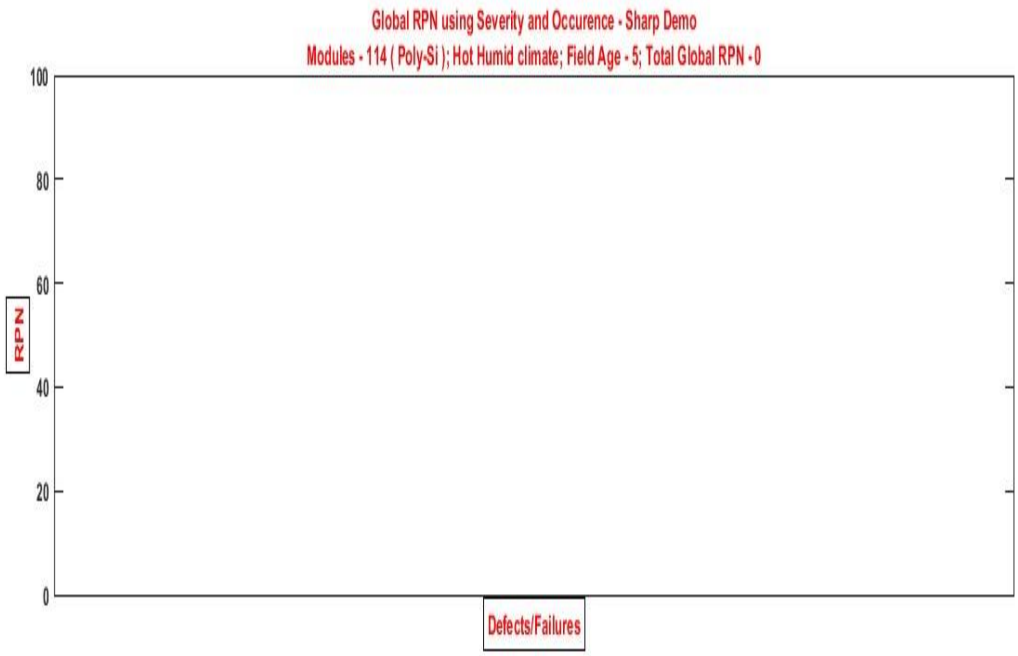

Global RPN - Yingli Demo
Modules - 74 (Poly-Si); Hot Humid climate; Field Age - 5; Total Global RPN - 0
RPN
1000
800
600
400
200
0
Defects/Failures

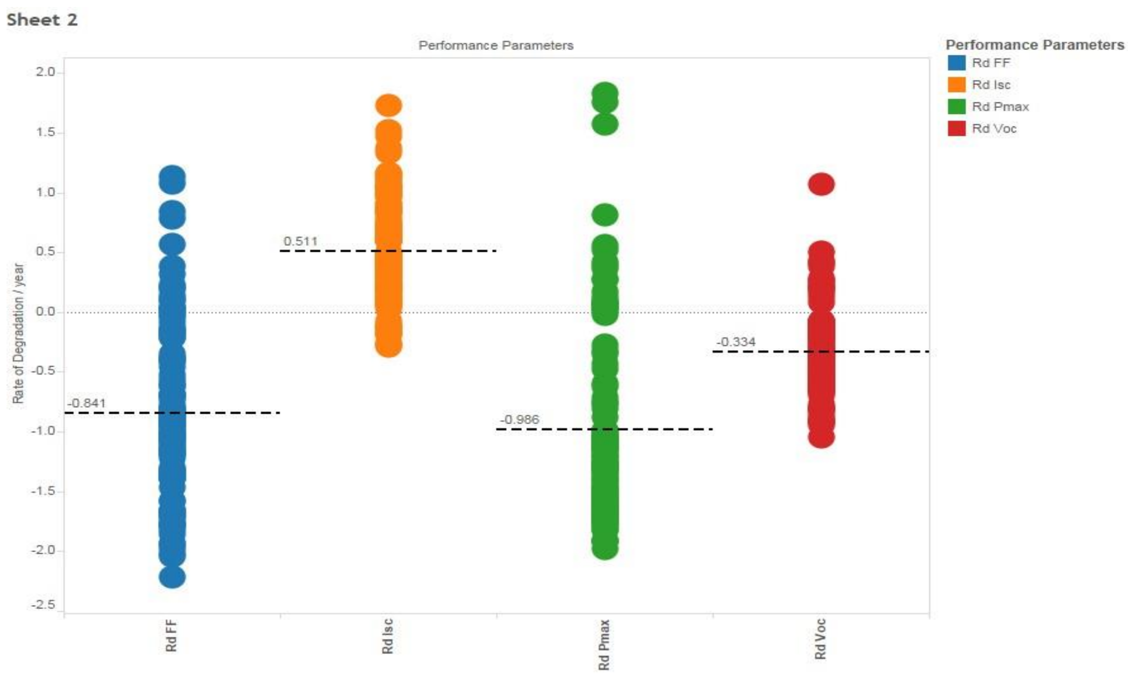

Sheet 1
Performance Parameter
Performance Parameter
Rd FF
Rd Isc
Rd Pmax
Rd Voc
Rate of degradation/year
2.5
2.0
1.5
1.0
0.5
0.0
-0.5
-1.0
-1.5
0.806
-0.395
1.219
0.740
Rd FF
Rd Isc
Rd Pmax
Rd Voc

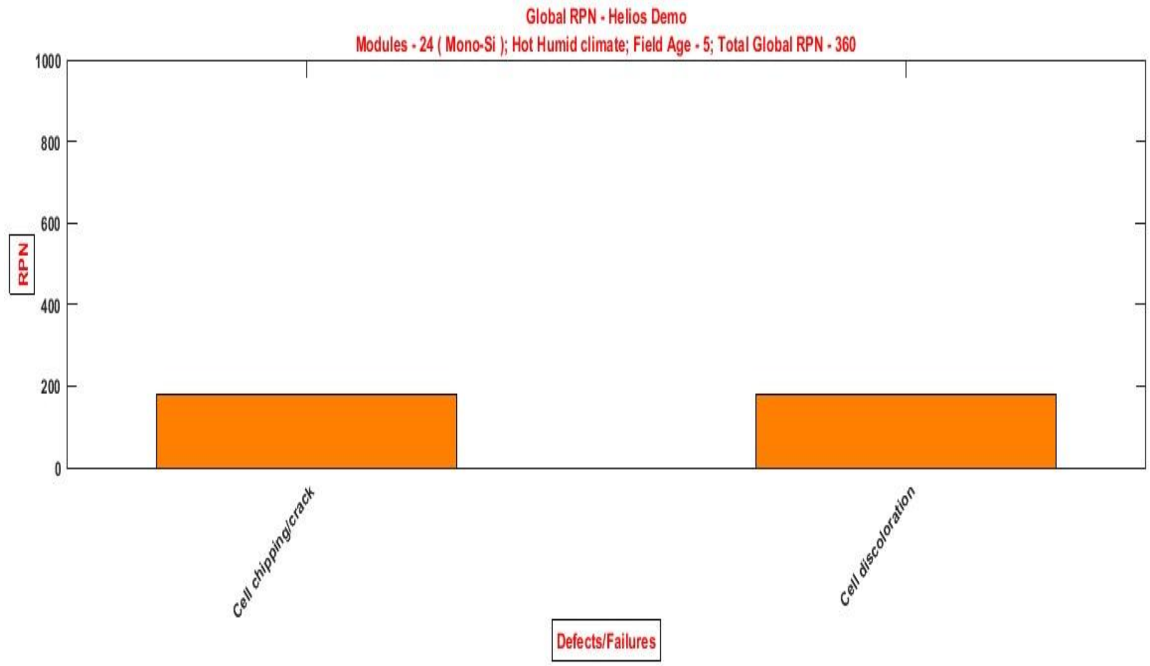

Global RPN - Yingli Demo
Modules - 74 (Poly-Si); Hot Humid climate; Field Age - 5; Total Global RPN - 0
RPN
Defects/Failures

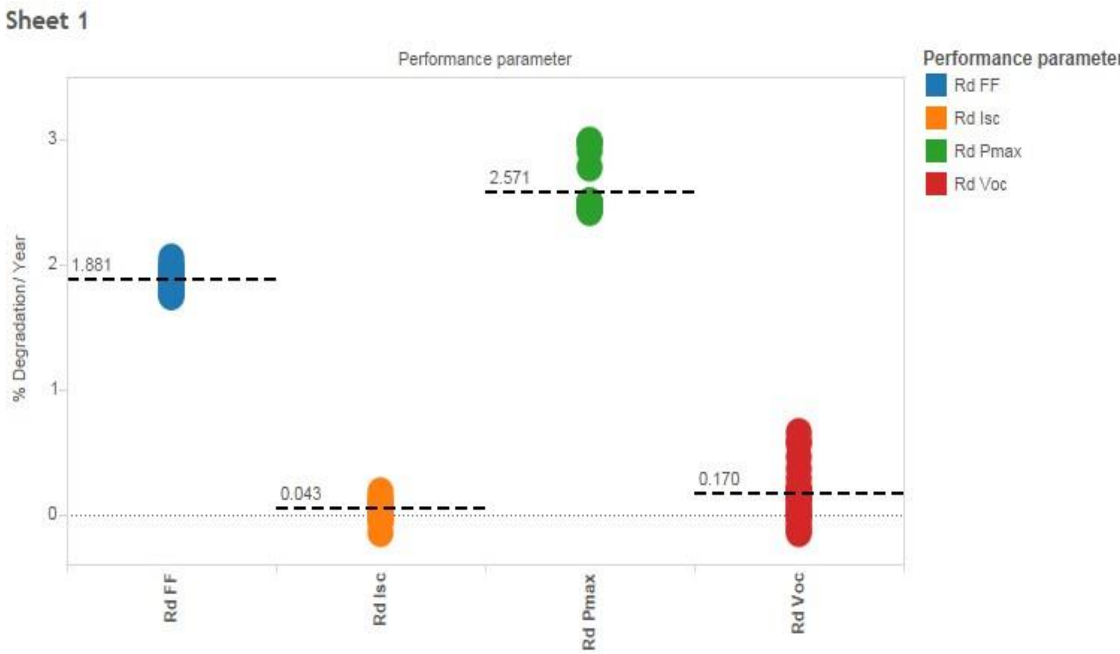
Sheet 1

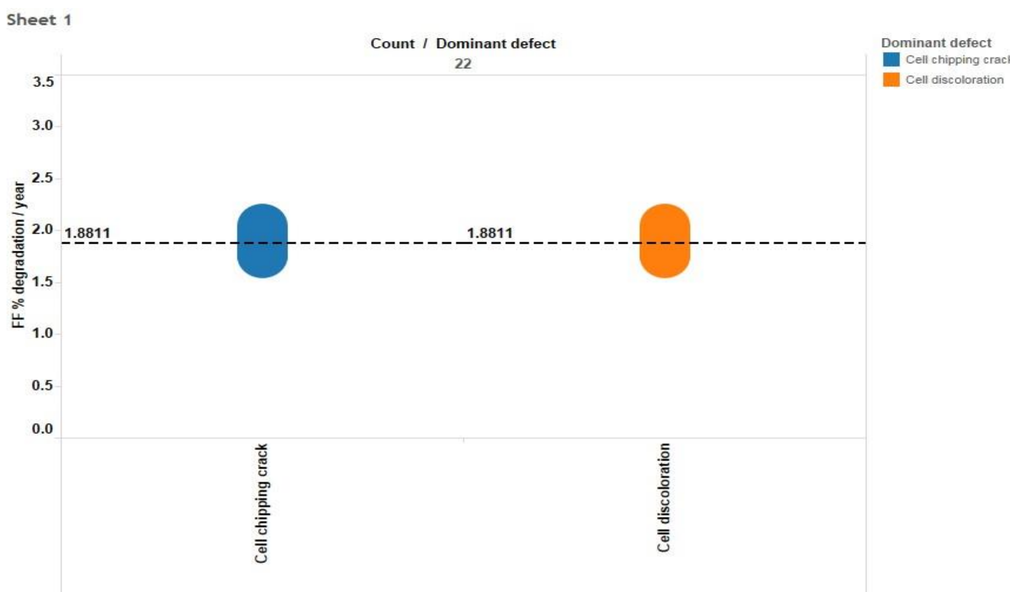

Performance parameter
% Degradation/Year
1.084
1.132
0.249
-0.275
Rd Isc
Rd Pmax
Rd Voc
RdFF
Performance parameter


Global RPN using Severity and Occurence - Sharp Demo
Modules - 114 (Poly-Si); Hot Humid climate; Field Age - 5; Total Global RPN - 0
RPN
Defects/Failures
100
80
60
40
20
0


Sheet 2
Performance Parameters
Performance Parameters
Rd FF
Rd Isc
Rd Pmax
Rd Voc
Rate of Degradation / year
0.511
-0.841
-0.986
-0.334
Rd FF
Rd Isc
Rd Pmax
Rd Voc


Global RPN - Helios Demo
Modules - 24 (Mono-Si); Hot Humid climate; Field Age - 5; Total Global RPN - 360
RPN
1000
800
600
400
200
0
Cell chipping/crack
Cell discoloration
Defects/Failures


Sheet 1
Performance parameter
Performance parameter
Rd FF
Rd Isc
Rd Pmax
Rd Voc
% Degradation / Year
3
2
1
0
1.881
0.043
2.571
0.170
Rd FF
Rd Isc
Rd Pmax
Rd Voc


Sheet 1
Count / Dominant defect
22
Dominant defect
Cell chipping crack
Cell discoloration
FF % degradation / year
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
1.8811
1.8811
Cell chipping crack
Cell discoloration